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Essays on Firm Behavior in International Trade

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PhD in Economics | Akin A. Cilekoglu

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Motivation and the State of the Art

International trade experienced an unprecedented growth and the world economy has been more integrated than ever before in the last decades. The ratio of world trade to world GDP, a measure that reflects the degree of the integration in the global economy, soared dramatically from 1980s until the 2008 financial crisis (Irwin, 2022). The share of world trade in world GDP increased from 13.7% in 1970 to 29.7% in 2018 (Antràs, 2020). By 2022, the value of world trade has seen roughly 4500% growth from 1950 levels.[1] From early 1990s until the 2008 financial crisis, trade in manufacturing goods dramatically increased from $740 billion in 1980 to $19 trillion in 2018 (Dorn and Levell, 2021).

Since the 1980s, we have witnessed an era of globalization in which goods, services, capital and labor flowed across national borders inconceivably. The establishment of the European Economic Community (1986), the North American Free Trade Agreement (1994) and the creation of the World Trade Organization (1995) paved the way for a new world trade system. Many countries in the developing world underwent an extensive trade liberalization episodes and adopted market-oriented policies (Dornbusch, 1992; Irwin, 2022). Regional trade agreements expanded and tariffs fell significantly (Colantone et al., 2022). Weighted average tariff applied on globally traded manufactured goods declined from 13.6% in 1986 to 5.2% in 2017 (Antràs, 2020).

[1] See WTO statistics in this link: `https://www.wto.org/english/res_e/statis_e/trade_evolution_e/evolution_trade_wto_e.htm`

In addition to falling tariffs, the world economy witnessed a massive technological change and transformation in patters of trade during this period, which contributed to the growth of world trade dramatically. Technological advances induced the fragmentation of the production within and across the national borders and the emergence of Global Value Chains (GVCs). Reduced transportation and communication costs due to new technologies facilitated the changes in the organization of production, trade and investment patterns (e.g. Hummels, 2007). Firms all around the world have become integrated into the GVCs and created complex trade networks.

As the GVCs has become the main paradigm of the global economy, trade in intermediate inputs dominated the international trade. In fact, the expansion in world trade during the last decades and the slowdown since the Great Recession coincide with the rapid growth of GVCs (Antràs, 2020). Between 1980 and 2015, the share of GVCs in world trade increased from 41.4% to 48.1% (Dorn and Levell, 2021). The measures of Johnson and Noguera (2012) suggest that roughly two-thirds of world trade today is carried out in trade of intermediate inputs.

During the last decades, the nature of world trade transformed dramatically. Technological improvements encouraged trade activities through lower shipping and communication costs, allowed new firms and countries to join the global trade and modified the patterns of specialization. Firms have been reorganizing and fragmenting their production processes and increasingly sourcing their intermediate inputs from suppliers across distinct locations. As a result, trade in intermediate inputs in the form of arms-length relationship and foreign direct investment (FDI) has been growing substantially. Firms took the advantage of international cost differences between countries by carrying out different stages of production across distinct locations. Thus, the possibility of reorganization of production beyond borders have been profitable for firms in developed countries as they could obtain the inputs for their production in a more cost-effective way.

The long history of trade literature has tried to explain the patterns of trade and its implications. Traditional Trade Theory is based on the idea of comparative advantage. Ricardian theory emphasizes the differences in opportunity costs of production and explains comparative advantage by the differences in productivity. On the other hand, Heckscher–Ohlin model explains comparative advantage by the differences in production factor intensities or factor endowments. In these models, factor endowments and specialization across industries and countries determine the patterns of trade. Each country produces the products and services that is comparatively best at, i.e. countries export in some industries and imports from others. Trade ultimately affects relative demand for factors of production and generates efficiency gains.

In the 1980s, the contributions of Krugman (1980), Helpman (1981) and Ethier (1982) introduced the New Trade Theory mainly because of the fact that a significant proportion of world trade occurred between similar countries, i.e. not giving a strong support to comparative advantage based models. They used the notions of increasing returns to scale instead of constant returns to scale, product differentiation and monopolistic competition to explain within-industry heterogeneity in their models. They show that differences in productivity (Ricardian theory) or factor endowments (Heckscher-Ohlin theory) may not necessarily determine the trade flows. Countries and industries with identical productivity or factor intensities can specialize in production of a particular product, and trade differentiated products with each other.

The emergence of micro datasets in 1990s allowed international trade literature to study firms and products instead of industry and countries. Empirical studies using these micro datasets documented substantial within-industry heterogeneity in terms of firm size and productivity and showed that firms involved in trade activities differ from those concerned with firms and consumers in domestic market. More specifically, researchers explored that exporters and importers differ from non-exporters and non-importers in various respects. Largely because of the discovery of heterogeneity among firms involved in trade, both empirical and theoretical research in trade literature since 2000s increasingly focused on the behavior of firms rather than analysing cross-industry and cross-country trade flows. Mainly with the contributions of Melitz (2003) and Antras and Helpman (2004), trade theory began to focus on the behavior of individual firms engaged in international trade at the beginning of 2000s, putting emphasize on both the trade in final goods and intermediate inputs.

In addition to developments in trade theory, empirical studies on intra-industry trade discovered considerable amount of evidences on firms. Exporting and importing firms represent a small fraction of the firms in the economy and they account for a substantial share of aggregate trade (e.g. Bernard et al., 2018). Firm heterogeneity is prevalent even in narrowly defined industries. Firms engaged in trade activities such as exporting, importing and FDI are not random sample of firms. They are larger, more productive, more skill-intensive, more capital intensive and they pay higher wages than non-exporters and non-importers.[2] According to this strand of literature, trade generates welfare gains through within-industry efficiency gains from intra-industry resource reallocation (e.g. Pavcnik, 2002; Melitz, 2003; Bernard et al., 2003) and within-firm productivity gains (e.g. Lileeva and Trefler, 2010; Bustos, 2011; Atkin et al., 2017).

Despite the empirical evidences documenting negative outcomes of trade on labor markets (e.g. Goldberg and Pavcnik, 2007; Autor et al., 2016), empirical and theoretical studies typically find that international trade induces productivity improvements and efficiency gains for firms. Economists argue that this positive impact of trade occurs for several reasons. The expansion of market size raises competition with foreign producers and more competitive environment can encourage entrepreneurial activities. While comparative advantage through specialization patterns can allow firms to exploit returns to scale and raise productivity, a more integrated economy allows the diffusion of knowledge and technology and contribute to productivity growth. Finally, increasing competitive pressure on monopolist tendencies in the domestic market leads to higher welfare through resource reallocation.

1.2 Objective and Structure of the Thesis

All around the world, access to international trade helped firms to produce their products more efficiently, conduct innovative activities, create more jobs, invest and increase human capital, become more environmentally friendly and increase the quality of their products. Successful firms reaped substantial gains from international trade for the decades but unproductive and inefficient firms could not survive and disappeared from the market.

Firms are the actual actors that determine trade flows and micro organisms of the international trade architecture. They shape trade networks and form GVCs by organizing their production across distinct locations. Since global trade consists of firm to firm transactions, researches using firm-level datasets can evaluate the gains from trade more effectively. Economists can better inform the policymakers, address the discontents of globalization and minimize the impacts of disruptions in GVCs. Therefore, examining the firm behavior is vital for trade studies to understand the dynamics in product and labor markets as well as con-

[2] See Bernard et al. (2007) and Bernard et al. (2012) for reviews on the topic.

sumer behavior more easily.

This thesis aims to provide evidences on the implications of firm behavior in international trade and the effects of firms' trade activities on their performance and labor market outcomes. I focus on the impact of technological adoption on global sourcing strategies in Chapter 2, the role of export destination on upgrading activities Chapter 3, the relationship between exporting and labor market power in Chapter 4. All three papers in this dissertation thesis investigate the trade with low-income countries using a rich firm-level dataset that incorporates the vast amount of information on Spanish manufacturing firms. For the identification of exogeneous changes in firm behavior, each chapter relies on external shocks to firms (technological advances in Chapter 2, real effective exchange rate movements in Chapter 3 and China's accession to WTO in Chapter 4).

This thesis contributes to the literature by expanding our knowledge about firms' behavior involved in international trade. I examine the causes and consequences of firm behavior in trade activities and how firms' decisions shape international trade flows. The findings in this thesis highlight the characteristics of exporting and importing firms. I document new evidences on the implications of firms' behaviour involved in international trade: how new technologies affect firms' decisions on production organization, how exporting affect firm upgrading depending on export market destination and how exporting affects labor market monopsony power.

Chapter 2 of the thesis is entitled *The Impact of Robot Adoption on Global Sourcing*.[3] We study the impact of robot adoption on firms' sourcing activities (foreign outsourcing, foreign vertical integration, domestic outsourcing and domestic vertical integration) between 2006 and 2016. We develop a theoretical model and analyse the channels that may affect the reshoring decisions of firms. We further empirically examine how intermediate input imports of robot adopters involved in various sourcing strategies. To identify the exogenous changes in robot adoption decisions, we utilize an instrumental variable strategy. We further test the robustness of our results using the imports from the low-income countries.

Dramatic increase use of industrial robots since 2000s underlined the possibility of disruptions in GVCs through reshoring activities of firms from developed countries. The main concern has been that industrial robots can be capable to perform the tasks performed by offshore workers and firms can reduce the interme-

[3] In this paper, I co-authored with my PhD advisors Raul Ramos and Rosina Moreno.

diate input costs by producing them using robots in the home country instead of sourcing them from suppliers located in offshore countries. Hence, firms' reshoring decisions might wipe out jobs once created by offshoring if industrial robots can substitute offshore workers.

Our paper contributes to the literature by showing that robot adoption did not reduce foreign sourcing activities at the firm-level, i.e. indicating that Spanish manufacturing firms did not reshore their production between 2006 and 2016. In contrast, we document that robot adopters increased their foreign sourcing activities as they produced larger output, contributing to the expansion of world trade. Different than many previous studies, we approach the issue from the perspective of labor demanding firms rather than local labor markets in offshore countries and therefore abstract from the characteristics of host countries.

Although exporters typically have common attributes with importers, most of the empirical studies in trade investigated exporting and largely neglected importing until recent years, mainly because of data restrictions. Moreover, imports of final and intermediate goods are not easily classified empirically but the dataset I use identifies whether firms obtain their intermediate inputs from foreign or domestic suppliers and whether these suppliers are their own subsidiaries or independent than sourcing firms.[4] This paper provides additional information to the literature about robot adopting firms involved in importing.

In single-authored Chapter 3 titled as *Export Destination and Firm Upgrading: Evidence from Spain*, I study whether the destination of exports is key to productivity improvements or not. I use the movements in real effective exchange rate (REER) during the 2008-2012 period to identify differential effects on exports to low-income and high-income countries. I take advantage of unique richness of the dataset and use various measures to examine firms' productivity and innovation performances, upgrading activities and efforts.

Empirical evidences suggest that exporters are more productive than non-exporters. Yet, the ambiguous question is whether this is because of some specific characteristics of exporters or because exporting raises productivity through learning or technology adoption. To provide a proper answer to this, the economists

[4] As reviewed by Johnson (2018), macro studies focusing on intermediate input trade utilise bilateral trade data to construct national input-output tables across borders. In contrast, micro-level studies rely on firm-level datasets that includes information on input sourcing decisions of firms and the organization of their production across distinct locations. Our analysis is in the latter group of studies.

rely on exogenous factors such as real exchange movements, trade liberalization episodes and tariff changes to identify the causal relationship.

A growing body of literature reveal that the destination of export market can give an answer to many unanswered questions. The evidences suggest that export destination may explain the productivity differences between firms through the differences in quality and prices for firms' inputs and outputs. As the argument goes, willingness to pay for higher quality products, competitive pressures and other market conditions may vary depending on the export market destination and ultimately affect productivity improvements of the firm.

Large majority of studies in the literature focused on firms exporting to destinations similar to (e.g. Lileeva and Trefler, 2010; Bustos, 2011) or richer countries (e.g. Van Biesebroeck, 2005; Atkin et al., 2017). One exception is the analysis of Park et al. (2010) who investigate foreign owned firms in China. However, empirical evidences suggest that foreign owned firms are better performing and more productive than domestic firms regardless of where they export to. Chapter 3 differs from these studies by examining the effects of exports from Spain to less developed countries on firms' performance and focusing on domestically owned firms.

I also contribute to the literature by studying the impacts of exporting on firm performance. Researchers usually use total factor productivity (TFP), adoption of or spending for new technologies, patents and R&D expenditures as a measure of productivity improvements and upgrading activities. Chapter 3 differs from other papers in the literature and utilizes the data on direct measures of firm upgrading and upgrading efforts.

The title of Chapter 4 is *Labor Market Monopsony and Firm Behavior: Evidence from Spanish Exporters*. In this paper, I develop a model that allows to measure the effect of a firm activity on its labor market monopsony power. The proposed framework is applicable to any firm behavior that might affect its labor market monopsony power. Exploiting China's accession to WTO in 2001, I employ the method to investigate how larger exports affected monopsony power of Spanish manufacturing firms between 1996 and 2007. I further analyse the potential channels that might be related to increased monopsony power.

Labor market monopsony has been a concern to many economists since decades. The idea was originally introduced by Robinson (1933) but little contribution has been made until 1990s. Large majority of studies primarily relied on the assumptions of frictionless labor markets, full employment and competitive wage.

However, recent years have received a growing attention on imperfect labor markets because rising market power of firms in product markets coincided with some labor market irregularities such as wage inequality, persistent unemployment, ineffective labor market policies and declining labor share. Today, a rapidly growing literature document that employers have some market power in the setting of wages.

Large amount of studies show that search frictions, idiosyncratic preferences, employer concentration, tax changes, institutional settings and legal restrictions to mobility may increase firms' bargaining power in wage setting and generate imperfections in labor markets. Although labor market monopsony has not been subject to antitrust issues in the past, antitrust authorities recently began to scrutinize anti-competitive behavior of firms in labor markets.

A substantial progress has been made in the ability of researchers to develop new theory and new empirical tools for measuring and identifying labor market monopsony power since 1990s. I contribute to this literature by providing a new method to implement in empirical studies. As an extension of standard monopsony model, my approach differs from the existing methods in a way that it estimates the contribution of a firm activity to its labor market power, rather than solely measuring firm's monopsony power. In addition to labor supply elasticity, this framework incorporates the wage and employment elasticities to the firm activity. While being simple, the proposed framework relies on few reasonable assumptions and requires the variables available in most of the firm-level datasets.

Some economists began to consider the role of trade in increasing monopsony power of firms. Chapter 4 provides new evidences for this growing literature. This paper is related to the recent studies that investigate implications of China's accession to WTO but focuses on to what extent higher exports affected labor market monopsony power of Spanish exporters as global trade has become tougher after 2001. Moreover, the analysis in this paper differs from those studies in that it spans a longer period and examines the labor market conditions in a developed country.

Chapter 5 is the conclusion of the thesis. Section 5.1 summarizes the findings of each chapter. Section 5.2 discusses the results of the analyses, their relevance with other studies in the literature and policy implications of the evidences. Finally, Section 5.3 presents the topics I consider studying in the future research projects.

Chapter 2

The Impact of Robot Adoption on Global Sourcing

2.1 Introduction

Advanced technologies have transformed the organization of production in manufacturing industry during the last decades. Developments in communication and information technologies have accelerated the expansion of production fragmentation and formed global value chains (GVCs) (e.g. Hummels et al., 2001; Johnson and Noguera, 2017). Sourcing intermediate inputs within and across national borders emerged as an attractive form of organizing the production for firms and became dominant feature of international trade. Firms in developed countries gained comparative advantage in terms of labor costs by relocating certain production processes to developing countries and created new job opportunities for offshore workers.[1]

In the meantime, robotics technology improved dramatically since 1990s and industrial robots have become more prevalent in production facilities across many industries. Robots are considered as sophisticated labor-saving technologies because their actions can be modified to perform different tasks without requiring

[1]A group of studies regarding production fragmentation focuses on labor market outcomes of offshoring tasks to low-income countries, see Crinò (2009) and Hummels et al. (2018) for comprehensive reviews of this literature. Another group focuses more on firms' decisions on sourcing inputs and contractual frictions, with Helpman (2006) and Antràs and Yeaple (2014) providing extensive reviews of this literature. Our paper is closer to the latter group.

human intervention.[2] Recent studies show that robots reduce employment and depress wages of low-skilled labor in manufacturing industry (e.g. Dauth et al., 2017; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Even though sourcing intermediate inputs produced by cheaper workforce in low and middle-income economies has become a major profitable strategy in international trade, robots offered firms an alternative channel for reducing labor costs. Since robots can substitute particularly low-skilled workers, they can make offshore workers in developing economies redundant if they enable firms to produce intermediate inputs instead of sourcing them from elsewhere. Thus, rapid increase in use of robots and their recently explored displacement effects raised the concerns over the potential disruptions in GVCs and the possibility of widespread reshoring activities of firms in developed economies (e.g. De Backer et al., 2016; Rodrik, 2018; Lund et al., 2019).

In this paper, we study how adopting robots has affected sourcing activities of Spanish manufacturing firms from 2006 to 2016. We present a simple model and use a unique firm-level panel dataset that allows us to assess the impact of robots on intermediate input demand for various sourcing strategies: foreign outsourcing, foreign vertical integration, domestic outsourcing and domestic vertical integration.[3] Using the instrumental variable strategy in our empirical analysis, we find that adopting robots increased the sourcing activities from foreign suppliers but did not affect sourcing from domestic suppliers. Our findings are robust to imports from low-income countries and various shocks. Hence, the results in this paper indicate that adoption of robots did not lead Spanish manufacturing firms to reshore production between 2006 and 2016.

The main contribution of this paper is to provide a firm-level evidence for

[2] In ISO 8373, The International Organization for Standardization defines an industrial robot as "an automatically controlled, reprogrammable, multipurpose, manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications".

[3] Outsourcing is a sourcing strategy defined as purchasing the intermediate inputs from an unrelated party, an independent supplier. On the other hand, vertical integration is a sourcing strategy in which the production of the intermediate inputs occurs within the boundaries of the firm through a related party. If intermediate inputs are imported from a foreign country, vertical integration and outsourcing are also referred as foreign direct investment (FDI) and offshoring (arm's-length relationship), respectively. Since our data allow us to identify both forms of sourcing and the location of suppliers, we prefer to use outsourcing and vertical integration to be more explicit.

the impact of labor-saving technologies (robot adoption) on sourcing decisions. Current studies are predominantly conducted at the macro-level, estimating the effects of exposure to robots in developed countries on industry-level trade with and regional labor markets of developing countries. We are able to approach this issue at the micro-level focusing on firms' input demand and identify the changes in different sourcing strategies. Hence, we analyse whether robot adopting firms reshored their previously offshored production by reducing intermediate input purchases from suppliers and how their sourcing activities changed subsequent to adoption decision. The variables in our dataset allow us to eliminate biases arising from the characteristics of individual countries involved in GVCs because participation in GVCs varies depending on the technological sophistication in production, specialization and natural resources across countries.

The rest of the paper is organized as follows. First, Section 2.2 provides an overview of the state-of-the-art of several strands of literature that are relevant in the context of our study. In Section 2.3, we present the theoretical framework and discuss various channels that may affect firms' decision on sourcing after adopting robots. Section 2.4 describes our data and documents stylised facts about the patterns of adoption and sourcing in Spain. In Section 2.5, we present our empirical analysis and the obtained results. Finally, Section 2.6 concludes.

2.2 Literature Review

2.2.1 Sourcing, trade liberalization and technology adoption

Sourcing activities typically occur in form of vertical integration or outsourcing. A vertically integrated firm owns the production of intermediates located elsewhere and the input supplier becomes related party to the sourcing firm by ownership. On the other hand, an outsourcing firm finds a suitable partner and subcontracts with an independent supplier to purchase intermediate inputs. In outsourcing, transactions involve two independent firms whereas trade occurs between two affiliated firms in vertical integration.

Firms' decisions on both technology adoption and sourcing are predominantly motivated by getting lower marginal costs. In theoretical models of sourcing, the technology used by firms determine their productivity levels and the organization of production across different locations (e.g. Antras and Helpman, 2004; Grossman and Rossi-Hansberg, 2008; Costinot et al., 2013). Despite the central role of technology in the literature of sourcing, empirical evidences for these predictions have been limited. Studying Danish firms, Bøler et al. (2015) find that a reduction in R&D costs promotes international sourcing activities and increases imports of intermediate inputs. Fort (2017) shows that advanced technologies facilitate production fragmentation among US firms by reducing communication and coordination costs. In addition to information and communication technologies, there has been an extensive usage and advances in automation technologies in recent times, specifically in robotics. Displacement effects of industrial robots sparked interest in not only how they affect labor markets in domestic economies, but also how they affect firms' organizational decisions and trade in intermediate inputs.[4]

Empirical evidences also suggest that trade liberalization encourages firms to adopt advanced technologies through new export opportunities (e.g. Lileeva and Trefler, 2010; Bustos, 2011) and import competition (e.g. Bloom et al., 2016). Recently, Bernard et al. (2020) find that offshoring firms increase their skill intensity and reorganize their resources toward more quality upgrading and innovative activities. However, given different characteristics of sourcing activities, firms' responses to trade shocks may vary depending on whether they are involved in related-party (vertical integration) or arm's-length relationship (outsourcing) (e.g. Bernard et al., 2009).

A considerable amount of studies previously focused on foreign sourcing activities such as foreign outsourcing and foreign vertical integration, but domestic sourcing strategies have usually been neglected. A notable exception is Fort (2017) who finds that advanced technologies favour domestic sourcing more than offshoring in the U.S. and create bias in sourcing decisions toward high human capital countries. Moreover, Kee and Tang (2016) document that trade liberalization increased the domestic content in exports and improved the activities of Chinese firms in global value chains.

The literature recently focused on how robots affect trade in intermediate inputs and provided mixed evidence on the role of robots in firms' cross-border activities. Several macro-level studies find negative effects of robots on local labor

[4]Particularly COVID-19 pandemic accelerated the concerns over disruptions in GVCs and potential slowdown in international trade because many firms began considering reducing their dependency on input suppliers across borders.

markets in Mexico (e.g. Artuc et al., 2019; Faber, 2020), in Colombia (e.g. Kugler et al., 2020) and across countries (e.g. Krenz et al., 2021). In contrast to these macro-level studies favoring reshoring trends, Antràs (2020) argues that a fall in participation in global activities is not apparent yet at the aggregate level and a body of literature finds positive effects of robots on imports from low-income countries (e.g. Artuc et al., 2018; Stapleton and Webb, 2020) and employment in Brazil (e.g. Stemmler, 2019).

Some studies investigated the impacts of robots on firm characteristics. Acemoglu et al. (2020) and Bonfiglioli et al. (2020) document that robot adopters increase their productivity and size. Domini et al. (2021) find that adoption of automation technologies increase a firm's net employment growth but do not change the skill composition of French manufacturing firms involved in international trade. Similarly, Humlum (2019) finds that robot adoption increased productivity but widened the wage gap between high and low-skilled workers in Denmark.

Previous theoretical and empirical studies demonstrate that technological developments predominantly foster sourcing activities. One group of empirical studies on robots shows that increased robot usage may increase or decrease intermediate input trade while another group of researches shows that robots may have favourable or detrimental outcomes in labor markets of developing countries. Our study examines whether and how firms changed their purchases of inputs from suppliers after adopting robots. We show that offshoring has not become less attractive for robot adopting Spanish firms as reshoring concerns argue. On the contrary, we find that robot adoption augmented intermediate input sourcing between 2006 and 2016 in our sample.

2.2.2 Evidence for Spanish firms

There are several papers which used the same Spanish firm-level data to investigate the effects of robots as we do. First, Koch et al. (2021) developed a Melitz-type model relying on a task approach similar to Acemoglu and Restrepo (2020). Confirming their predictions from the model, their empirical results for the 1990-2016 period using longitudinal data from the ESEE demonstrate that high productivity firms tend to adopt robots. Furthermore, robot adopters gain competitive advantage due to increased output and grow in size over time at the expense of non-adopters. Regarding the firms involved in trade activities, they found that only exporters among robot adopters could raise their TFP.

Second, Alguacil et al. (2022) studied the effects of robots on exports at the intensive and extensive margin from 1990 to 2014. To overcome the endogeneity problem, they combine propensity score matching with difference-in-differences estimation as in Koch et al. (2021). Their findings show that robot adoption increases exports while raising the probability of entry to foreign markets for both exporting and importing.

Finally, our paper is more closely related to Stapleton and Webb (2020) but exhibits many differences. Their objective is to analyse how automation has affected trade and multinational activity with lower-income countries between 1990 and 2016. In contrast to rising concerns over reshoring activities, they find that automation technologies affected imports and number of affiliates of Spanish firms positively. Taking this into account, one main difference of our study is that we investigate the changes in firms' various sourcing strategies distinguishing input suppliers' location and their relationship with sourcing firms for the 2006-2016 period.

Our paper also differs from Stapleton and Webb (2020) in that they use multiple automation variables provided in the ESEE dataset such as robots, computer numerically controlled (CNC) machines and flexible manufacturing systems (FMS) rather than utilizing specifically the data on robot usage as in our analysis. Similar to Alguacil et al. (2022), they find that using automation technologies increased the probability of importing from low-wage countries between 1990 and 2016. In terms of the instrument used for the identification strategy, they use industry-level patent titles related to robotics inventions as a proxy for exposure to technological changes in robotics together with an alternative instrument using the same IFR dataset as in our analysis. However, we measure the firm-level exposure to technological changes by interacting the firm's share of imported technology in the industry with industry-level robot installations in several EU countries.

Some of the results shown by Stapleton and Webb (2020) are aligned with those of Koch et al. (2021). In contrast to our approach in theoretical framework relying on cost advantage and disadvantage of robot adoption for the sourcing firm, they develop a Melitz-type model analogous to Koch et al. (2021) using a task based approach. In their empirical analysis, they discover that most productive firms select into automation (e.g. Koch et al., 2021) and offshoring decisions while automated firms are more intensely involved in trade before automating their production processes.

The ESEE dataset allows us to investigate the effects of robot adoption on different sourcing strategies as it reveals the information on the relationship between the sourcing firm and the supplier. Whether a firm is outsourcing from or vertically integrated with foreign or domestic suppliers may be an important factor in determining a firm's reshoring decision because each of these sourcing strategies would incur various kinds of costs for reshoring. The literature has not yet come to a common conclusion of how robots affect firms' intermediate input trade activities involved in different sourcing activities. In this regard, we fill a notable gap in the literature using a unique Spanish firm-level data.

2.3 Theoretical Framework

This section presents a theoretical framework of robot adoption and the subsequent decision on sourcing activity. Robot adoption and potential reshoring decisions occur in a sequential order. Once the firm finds adopting robots profitable, the sourcing firm considers partially or fully reshoring the production of inputs.

Consider a manufacturing firm sourcing input X^s from a supplier located elsewhere denoted by s and carrying out the production of remaining input $X^{\mathbb{1}_R}$ when adopted robots and $\tilde{X}$ when not yet adopted robots itself in its headquarters. The firm ultimately utilizes these two components to obtain the final output of a sourcing firm, Y.[5] The relationship between supplier and sourcing firm may be in form of outsourcing or vertical integration while the supplier may be located in domestic country or in a foreign country. We assume in the model that there are no frictions in communication and shipping between the supplier and the sourcing firm. In assembly, composite inputs X^s and $\tilde{X}$ of a non-adopting sourcing firm transform into final output in following Cobb-Dauglas form $Y = (\tilde{X^s})^{\beta}(\tilde{X})^{1-\beta}$. We assume that adoption of robots do not alter the production structure, i.e. input shares in output β and $1-\beta$ remain the same when the firm adopts robots. The production function of a robot adopting firm is given as

[5]This final output may also be an input for another firm in the global supply chain, i.e. the sourcing firm may be a supplier to another firm. Since our focus is on whether a robot adopting firm may change its sourcing decisions, we remain agnostic on the case that the sourcing firm may be a supplier or subsidiary at the same time. We would like to thank a reviewer for reminding us to explicitly highlight this issue.

$$Y^{\mathbb{1}_R} = (X^s)^{\beta}(X^{\mathbb{1}_R})^{1-\beta}. \tag{2.1}$$

We assume that labor market of the intermediate input supplier is competitive. The composite intermediate input X^s is produced in CES form,

$$X^s = \left[\gamma\big(\Gamma^L L^s\big)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)\big(\Gamma^R \mathbb{1}_R R\big)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2.2}$$

where L^s denotes labor of supplier and R denotes robots of the sourcing firm. σ represents the elasticity of substitution between labor and robots. $\sigma > 1$ implies that robots and supplier's workers are gross substitutes such that robots can substitute supplier's workers because they perform the same tasks. On the other hand, $\sigma < 1$ implies that robots and supplier's workers are gross complements and sourcing firm's robots R cannot substitute supplier's labor L^s. Γ^L and Γ^R are the productivity parameters for labor and robots, respectively.

$\mathbb{1}_R$ is a dummy variable for robot adoption. $\mathbb{1}_R = 1$ indicates that the production of X^s is carried out partially or fully by robots of sourcing firm. In other words, the sourcing firm can reshore some of the tasks. $\mathbb{1}_R$ is equal to 0 if only supplier's workers are performing the tasks required to produce X^s.

Distribution parameter $\gamma \in [0, 1]$ reflects robot intensity in intermediate input production of X^s. $\gamma = 0$ implies that X^s is only produced by robots of sourcing firm. This is equivalent of reshoring all the production given by $X^s = \Gamma^R \mathbb{1}_R R$. On the other hand, $\gamma = 1$ implies that intermediate input is produced solely with workers of the supplier, $\tilde{X}^s = \Gamma^{L^s} L^s$.

In the context of our analysis, reshoring induces that robots can substitute supplier's workers employed for the intermediate input production of X^s. Thus, although robots enters into the production function of the supplier but investment costs in robots are incurred by the sourcing firm. We characterize the cost function of the supplier by

$$C^{X^s} = \tau^l w^s L^s \tag{2.3}$$

where w^s and L^s denote the wage and the employment of the supplier, respectively. Purchases from suppliers are subject to iceberg transport costs $\tau^l \geq 1$ where l is the index for the location of the supplier. We assume that sourcing inputs from a supplier located abroad entails trade cost $\tau^F > 1$ whereas sourcing inputs from a domestic supplier entails trade cost $\tau^D = 1$, i.e. there is no extra shipping costs for a domestic producer.

We assume that the price of intermediate input P^{X^s} is competitive. A profit maximizing supplier's labor demand can be expressed as

$$L^s = \frac{P^{X^s}(X^s)^{1/\sigma}\varphi^L}{\tau^l w^s} \tag{2.4}$$

where $\varphi^L = \gamma\big(\Gamma^{L^s}L^s\big)^{\frac{\sigma-1}{\sigma}}$ denotes the share of labor in production of input X^s. Similarly, we define $\varphi^R = (1-\gamma)\big(\Gamma^R \mathbb{1}_R R\big)^{\frac{\sigma-1}{\sigma}}$ as the share of sourcing firm's robots in production of input X^s. The sourcing firm that has not yet adopted robots produces certain inputs required for the final output with Cobb-Dauglas technology: $\tilde{X} = \tilde{A}\tilde{L}^{\alpha_L}\tilde{K}^{\alpha_K}$. On the other hand, a robot adopter produces the remaining inputs in the following form:

$$X^{\mathbb{1}_R} = AL^{\alpha_L}K^{\alpha_K} \tag{2.5}$$

where A is firm productivity, L is labor, K is capital, α_L is labor share in output and α_K is capital share in output.

For the sake of simplicity, we assume that using robots for the production of $X^{\mathbb{1}_R}$ is embedded in capital K. Since we are interested in how robots can substitute workers of a supplier, we abstract from substitution effect of robots on workers of the sourcing firm. Hence, we assume that adoption of robots does not change the production structure of $X^{\mathbb{1}_R}$, i.e. α_L and α_K remain the same following robot adoption decision. Moreover, following the recent empirical evidences (e.g. Acemoglu et al., 2020; Bonfiglioli et al., 2020; Koch et al., 2021), we assume that robot adoption increases productivity, $A > \tilde{A}$. This is an important element of our framework illustrating the increased productivity in final output. As the sourcing firm produces higher input $X^{\mathbb{1}_R} > \tilde{X}$, it demands more input $X^s > \tilde{X}^s$ to obtain more final output produced $Y^{\mathbb{1}_R} > Y$.[6]

We define the cost function of a non-adopter sourcing firm for the production of $\tilde{X}$ as $\tilde{C} = w\tilde{L} + k\tilde{K} + f^{s,l}$. The cost function of a robot adopter sourcing firm for the production of $X^{\mathbb{1}_R}$ is given by

$$C^{X^{\mathbb{1}_R}} = wL + kK + f^{s,l} + \mathbb{1}_R f^R \tag{2.6}$$

where w is the wage and k is the rental rate of capital of the sourcing firm.

[6] In support of this argument, using polynomial figures in the next section, we show that firm sales are linearly increasing with each sourcing activity.

We assume competitive markets in labor and capital of the sourcing firm, i.e. the prices of labor and capital are given to the sourcing firm and do not change with robot adoption decision. f^R denotes the fixed cost of robot adoption as in Yeaple (2005) and Bustos (2011), referring to the investment costs incurred once the robots are deployed in production. Notice that the fixed cost of adoption f^R in $C^{X^{\mathbb{1}_R}}$ represents the robot investments to produce $X^{\mathbb{1}_R}$ and not to produce the inputs provided by the supplier X^s. We will show below that at the stage the sourcing firm decides whether to reshore or not, an additional robot investments will be incurred to produce X^s alongside of f^R in $C^{X^{\mathbb{1}_R}}$.

$f^{s,l}$ is fixed cost of tangible and intangible assets in sourcing which needs to be incurred once a firm selects into sourcing. s indexes the form of sourcing activity and l indexes the location of the supplier. Fixed costs of sourcing consist of search costs, gathering information on potential suppliers, finding a suitable supplier location, building a buyer-seller relationship and investing in new physical assets, equipments and building new plants.[7] Thus, $f^{s,l}$ may vary if the sourcing firm is outsourcing or vertically integrated with the supplier and if the supplier is located in home or a foreign country. However, we do not assume any ordering on the size of fixed costs for each sourcing strategy for the sake of simplicity.

Robot Adoption Decision

Sourcing firm carries out investments in robots before considering reshoring the production. We can now describe an equilibrium with robot adoption decision of sourcing firm. Let $\pi^{Y^{\mathbb{1}_R}} = P^{Y^{\mathbb{1}_R}}(X^s)^{\beta}(X^{\mathbb{1}_R})^{1-\beta} - C^{X^s} - C^{X^{\mathbb{1}_\mathbb{R}}}$ be the profit function of a robot adopter and the profit function of a non-adopter can be expressed as $\pi^Y = P^Y(\tilde{X}^s)^{\beta}(\tilde{X})^{1-\beta} - C^{X^s} - C^{\tilde{X}}$. Notice that the sourcing firm does not yet attempt to substitute workers of the supplier and uses robots only for the production of $X^{\mathbb{1}_R}$. This induces that the cost of sourcing activity, C^{X^s}, or payments to the supplier does not change at this stage.

Suppose that $\pi^{Y^{\mathbb{1}_R}} > \pi^Y$, so that it is profitable for the firm to adopt robots. A firm adopting robots bears fixed technology costs $\mathbb{1}_R f^R$ embedded in $C^{X^{\mathbb{1}_\mathbb{R}}}$ but robot adoption may raise its revenue such that $P^{Y^{\mathbb{1}_R}}(X^s)^{\beta}(X^{\mathbb{1}_R})^{1-\beta} > P^Y(\tilde{X}^s)^{\beta}(\tilde{X})^{1-\beta}$,

[7] Similarly, Antras and Helpman (2004) defines fixed organizational costs of sourcing wf^s as the sum of supervision, quality control, accounting, marketing practices, search, monitoring and communication activities. See Antràs and Yeaple (2014) for other approaches defining fixed costs of multinational firms in trade.

making it profitable. Adopting robots may increase (or decrease) the costs of sourcing firm if adoption requires more (or less) workers, $L \geq \tilde{L}$, and capital, $K \geq \tilde{K}$. Notice that if an adopter lowers the demand for labor and capital, $L < \tilde{L}$ and $K < \tilde{K}$, the cost function may still be lower for an adopter, $C^{X^{\mathbb{1}_{\mathbb{R}}}} < \tilde{C}$, if the investments in robots f^R is sufficiently low. In such a case, adopting robots may be profitable even if the revenue does not change: $\pi^{Y^{\mathbb{1}_R}} > \pi^Y$ if $C^{X^{\mathbb{1}_{\mathbb{R}}}} < \tilde{C}$ and $P^{Y^{\mathbb{1}_R}}(X^s)^{\beta}(X^{\mathbb{1}_R})^{1-\beta} = P^Y(\tilde{X}^s)^{\beta}(\tilde{X})^{1-\beta}$.

For a sourcing firm, robot adoption decision is determined by the condition that profits in case of adoption and non-adoption balance off. We can use indifference condition for robot adoption to assess the relevant factors that can encourage firm to adopt robots at a point that profits are equal for an adopter and a non-adopter. From $\pi^Y = \pi^{Y^{\mathbb{1}_R}}$, we can obtain the robot adoption decision as

$$\mathbb{1}_R = \frac{\Delta\mathcal{R} - \Delta\mathcal{C}}{f^R} \tag{2.7}$$

where $\Delta\mathcal{R} = P^{Y^{\mathbb{1}_R}}Y^{\mathbb{1}_R} - P^Y Y$ and $\Delta\mathcal{C} = (wL + kK) - (w\tilde{L} + k\tilde{K})$. $\Delta\mathcal{R} - \Delta\mathcal{C}$ refers to the gains from adoption, which increases the adoption probability. $\Delta\mathcal{R}$ represents how much revenue increases after adopting robots whereas $\Delta\mathcal{C}$ represents how much the costs of labor and capital increase after adopting robots. Notice that adoption probability is higher with increases in revenue, $\Delta\mathcal{R} > 0$ and reduction in labor and capital costs, $\Delta\mathcal{C} < 0$. Since the input prices are competitive, increases in costs after robot adoption may arise only if the demands for inputs increase, $L > \tilde{L}$ and $K > \tilde{K}$. Finally, the gains from robot adoption are proportional to the investment costs in robots, f^R, and higher robot investments makes adoption more difficult, i.e. decreases adoption probability.

Reshoring Decision

Subsequent to robot adoption decision, sourcing firm considers whether to reshore previously offshored production located elsewhere. In practice, without a change in product or production technique, this can only be possible if the tasks that can be performed by robots of sourcing firm are identical to the tasks performed by the workers of the supplier. If and only if the tasks are the same, sourcing firm's robots can substitute supplier's workforce and make reshoring a feasible option.

Sourcing firm chooses whether to adopt robots $\mathbb{1}_R$ and how much to source intermediate inputs from elsewhere X^s to maximize its profits:

$$\max_{\mathbb{1}_R, X^s} \pi^{Y^{\mathbb{1}_R}} = P^{Y^{\mathbb{1}_R}} (X^s)^{\beta} (X^{\mathbb{1}_R})^{1-\beta} - C^{X^s} - C^{X^{\mathbb{1}_\mathbb{R}}} + \mathbb{1}_S \Big(\nu C^{X^s} - \rho C^{X^{\mathbb{1}_R}} \Big). \quad (2.8)$$

The last term $\mathbb{1}_S \Big(\nu C^{X^s} - \rho C^{X^{\mathbb{1}_R}} \Big)$ represents the gains from reshoring decision. The parameter $\mathbb{1}_S$ denotes the reshoring decision and takes the value 1 for reshoring and 0 otherwise. $1 \geq \nu \geq 0$ governs the cost advantage from reshoring production to home country. Sourcing firm reduces its costs from offshoring if it decides to bring back some of the production to home country, i.e. adding on firm profit by $\mathbb{1}_S \nu C^{X^s}$. The size of νC^{X^s} determines how much sourcing firm benefits from cutting foreign labor costs. $\nu = 1$ indicates that firm reshores all the production to its headquarters and the costs of producing X^s to the supplier C^{X^s} disappears from total profits $\pi^{Y^{\mathbb{1}_R}}$. On the other hand, $\nu = 0$ indicates that firm continues to sourcing input X^s from the supplier, therefore cannot make any cost savings from reshoring decision.

While saving from supplier's labor costs, the sourcing firm needs to carry out further investments to reshore production because of producing additional components and services that are previously sourced from the supplier. We denote additional fixed costs of investments by $\rho > 0$ that indicates how much additional costs firm has to incur if it decides to reshore. Additional fixed costs refer to investments in additional robots for producing X^s, building new factory or additional space for production, inventories, additional workers and technicians. We do not restrict the upper bound of ρ due to the fact that reshoring costs may exceed the initial costs of robot adoption.

The first-order conditions of this problem yield

$$P^{X^s} X^s = \mathbb{1}_R f^R \left(\frac{-1-\rho}{-1+\mathbb{1}_S \nu} \right) \left(\frac{\sigma}{1-\sigma} \right) \left(1 + \frac{\varphi^R}{\varphi^L} \right) \left(1 + \frac{\varphi^L}{\varphi^R} \right) \quad (2.9)$$

where the left hand side of the Equation (2.9) represents the total payments to the supplier for intermediate input purchases of X^s. This is what we observe in our dataset and use as the dependent variable in the empirical analysis. On the right hand side of the equation, $\mathbb{1}_R$ equals 1 if the sourcing firm adopts robots. Notice that conditional on robot adoption decision, investment costs in robots raises the purchases from suppliers $\partial(P^{X^s} X^s)/\partial f^R > 0$ because reshoring becomes more difficult due to the high costs of adopting robots. The term $\frac{\sigma}{1-\sigma}$ refers to substitution effect, indicating that firm continues sourcing inputs when robots and supplier's workers are complements ($\sigma < 0$) and reduces sourcing when robots and supplier's workers are substitutes ($\sigma > 0$). Given $0 \leq \nu \leq 1$, the term $\frac{-1-\rho}{-1+\mathbb{1}_S \nu} > 0$ corresponds to productivity effect because it proportions the cost of production with robots to suppliers. As defined in Equation (2.8), ρ augments the costs of production with robots and ν augments the gains from sourcing. Therefore, higher costs of producing with robots compared to sourcing makes production of inputs using robots less profitable and therefore increases sourcing due to productivity increase from using robots. Finally, the last two terms correspond to a constant as $\frac{\varphi^R}{\varphi^L}$ is the relative share of robots to supplier's workers and $\frac{\varphi^L}{\varphi^R}$ is the relative share of supplier's workers to robots in production of input.

Discussion

Theoretical framework presented in this section relies on production and investment costs in motivating the robot adoption and reshoring decisions of a sourcing firm. In the model, we emphasize the advantages and disadvantages of reshoring in terms of costs because after all, bringing the production back to home country must be more profitable for reshoring to be the optimal choice. On the other, while robots and tasks may not be substitutable at all (e.g. Domini et al., 2021), substituting tasks with robots is not a sufficient condition for a firm to reshore the production.

In our framework, two factors ultimately determine reshoring decision or continuing purchasing more intermediate inputs: elasticity of substitution between robots and supplier's workers, and relative cost of producing intermediate inputs with robots to a supplier. However, given the complexity of global value chains, there could be several other reasons. First, the characteristics of tasks performed by offshore workers and robots may be different and if this is the case, replacing robots with offshore workers may be difficult. While robots typically perform routine tasks, Blinder and Krueger (2013) show that routine tasks are not more likely to be offshorable with respect to other tasks.[8] Consistent with these findings, Stemmler (2019) recently identified that foreign robots increased employment in Brazil for largely non-routine tasks. Robots are typically expected to substitute low-skilled workers in developing countries but such substitution may not occur if

[8] According to some of their measurements, even larger share of non-routinisable jobs are offshorable compared to routinizable jobs.

fewer low-skilled workers are used in production of intermediates exported from developing countries to developed countries (e.g. Timmer et al., 2014) Similarly, Costinot et al. (2011) find that the shares of vertically integrated firms are higher in less-routine industries in the U.S. Thus, the tasks performed by offshore workers can actually have medium complexity, making substitution between robots and offshore workers difficult.

Second, even if we assume that tasks performed by offshore workers and robots are the same, it does not necessarily induce the substitution between them. Bernard et al. (2020) recently found that Danish firms continue producing and improving the quality of products that they once offshored. This suggests that reshoring may not occur even though robots become capable of producing the same imported intermediate inputs. Finally, international specialization can have a crucial role in the organization of supply chains across firms in different countries and lead to interdependencies across borders (e.g. Antras et al., 2017). Hence, interdependency of suppliers across different locations can also impair the possibility of reshoring decisions.

2.4 Data and Stylised Facts

We use firm-level data from the ESEE (Encuesta Sobre Estrategias Empresiales), a panel dataset of Spanish manufacturing firms collected by Fundacion SEPI and the Spanish Ministry of Industry. The survey spans the 1990-2016 period, distinguishes 20 manufacturing industries based on two-digit NACE classification (Classification of Economic Activities in the European Community) and contains a large sum of information on the characteristics of annually surveyed 1,800 Spanish firms with 10 or more employees.[9]

The ESEE is unique in that it conveys information on the sourcing strategies of firms: whether the firm purchases intermediate inputs from an unrelated party (*outsourcing*) or from a related party (*vertical integration*), and whether the supplier is located abroad or in Spain. We are not able to obtain any information about suppliers' characteristics and origin of their countries. However, our data contain the value of imports from specific locations which are used for robustness checks, namely Latin America and the rest of the world (defined as all the regions except Latin America, OECD and EU countries).

[9] https://www.fundacionsepi.es/investigacion/presentacion.asp

The ESEE dataset reports the value of total imports and total purchases of a firm in each year. Our main dependent variables are foreign sourcing strategies and domestic sourcing strategies. A foreign sourcing strategy is defined as the percentage of a foreign sourcing activity (intermediate imports) in total imports. Accordingly, foreign outsourcing is the percentage of intermediate input imports in total imports for a firm outsourcing from a foreign supplier and foreign vertical integration is the percentage of intermediate input imports in total imports for a firm vertically integrated with a foreign supplier. On the other hand, a domestic sourcing strategy is defined as the percentage of a domestic sourcing activity (intermediate input purchases) in total purchases. More specifically, domestic outsourcing is the percentage of intermediate input purchases in total purchases for a firm outsourcing from a domestic supplier and domestic vertical integration is the percentage of intermediate input purchases in total purchases for a firm vertically integrated with a domestic supplier. Since our dataset has the information on the values of total imports and total purchases, we can obtain the values of each sourcing strategy to use as dependent variables.

As our key explanatory variable, the measure of firm-level robot adoption is binary, indicating whether the firm used robots in production process in a given year. Unlike the large majority of current studies that rely on *exposure to robots* at the industry or regional level, we can identify the effects of robots explicitly at the firm-level. Our dataset contains further detailed information on imported technologies, intermediate consumption, materials price index, number of markets the firm is operating in, wage and skill intensity.

For the construction of our instrument, we combine the ESEE dataset with the IFR (International Federation of Robotics) database, which consists of new installations and the stock of industrial robots by industry, country and year. The IFR data cover 50 countries including Spain, and 35 industries within manufacturing from 1993 to 2014.[10] We evaluate the trends in Spain's intermediate input trade with other European Union countries (those selected in construction of our instrument) to test the robustness of the results. To do so, we obtain the data on aggregate intermediate input exports to Spain by country from the The World Integrated Trade Solution (WITS).

In our analysis, we use an unbalanced panel of the data and study the period

[10]See Table *A*1 in Appendix 2.A.1 for the details of matching of our two datasets based on industries.

2006-2016 for several reasons. First, information regarding the various sourcing strategies in the ESEE dataset are only available for this period. Second, reshoring narrative began to have widespread media coverage after the global financial crisis in 2008.[11] Indeed, Faber (2020) finds no effects of US robots on local labor markets in Mexico for 1990-2000 but for 2000-2015. Third, focusing on the 2006-2016 period allows us to abstract from the trade dispute between US and China that occurred during the Trump administration and COVID-19 pandemic.

Table 2.1 reports summary statistics for the participation in sourcing activities. The table shows that larger fraction of robot adopters purchased intermediate inputs than non-adopters regardless of sourcing strategy and import destinations. Outsourcing is a more common strategy than vertical integration among both robot adopters and non-adopters. Table 2.2 presents the intensities of sourcing between adopters and non-adopters across sourcing strategies. Adopters also appear to be sourcing more intensely than non-adopters on average while outsourcing firms purchase intermediate inputs more intensely than vertically integrated firms. These tables document that robot adopters are more actively involved in sourcing activities and outsourcing is more commonly preferred form of intermediate input trade.

Table 2.1: Participation Shares by Sourcing Strategies

	Robot Adopters			Non-Adopters		
	Mean	SD	Obs.	Mean	SD	Obs.
Foreign Outsourcing	0.577	0.494	5087	0.368	0.482	12086
Foreign Vertical Integration	0.175	0.380	5085	0.058	0.234	12085
Domestic Outsourcing	0.942	0.233	5112	0.926	0.262	12091
Domestic Vertical Integration	0.251	0.433	5112	0.100	0.301	12093
Rest of the World	0.286	0.452	9251	0.147	0.354	30223
Latin America	0.080	0.272	6367	0.040	0.195	15917

Note: This table presents the percentage of firms participating in sourcing strategies across the two groups between 2006 and 2016. Rest of the world represents the regions except Latin America, the OECD and the EU countries. SD denotes the standard deviations. Sourcing strategies and imports from low-income countries are provided in IHS transformed values.

[11] See Kinkel and Maloca (2009), Pisano et al. (2009), Sirkin et al. (2011) and Home (2013) for early concerns.

Table 2.2: Sourcing Intensities

	Robot Adopters			Non-Adopters		
	Mean	SD	Obs.	Mean	SD	Obs.
Foreign Outsourcing	8.767	7.719	5087	5.015	6.752	12086
Foreign Vertical Integration	2.814	6.173	5085	0.890	3.624	12085
Domestic Outsourcing	15.511	4.247	5112	13.634	4.280	12091
Domestic Vertical Integration	4.012	7.007	5112	1.534	4.649	12093
Rest of the World	4.172	6.709	9251	2.031	4.969	30223
Latin America	1.134	3.886	6367	0.537	2.692	15917

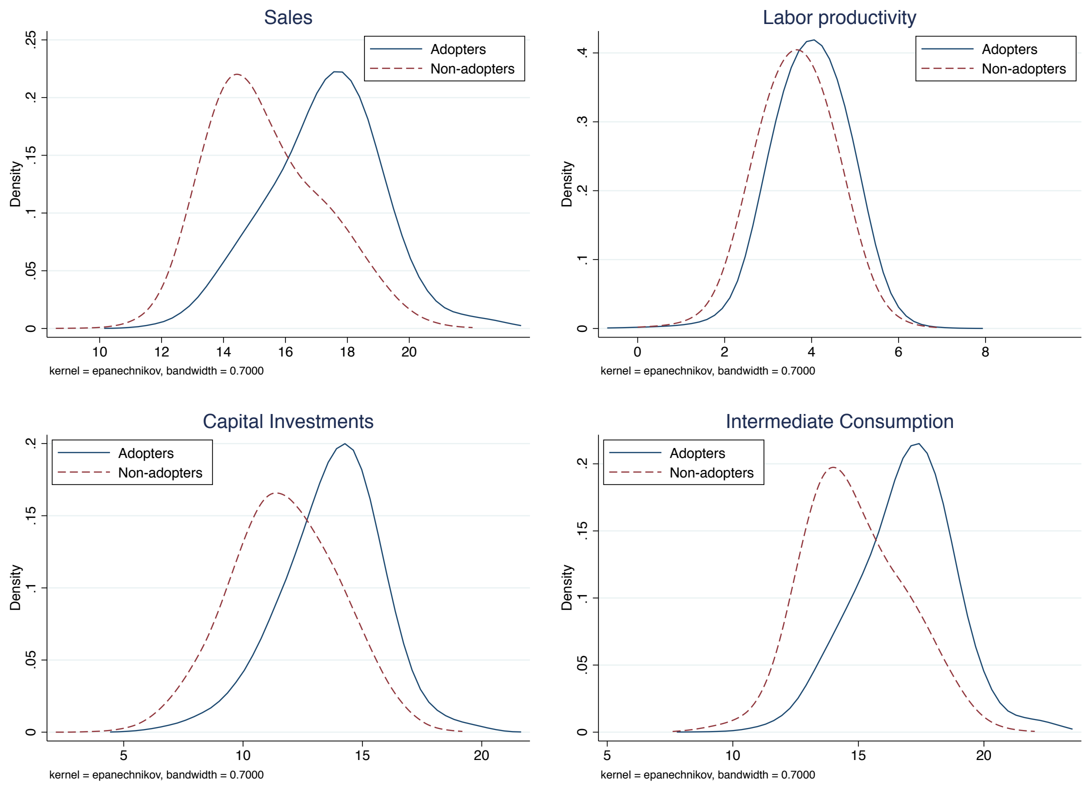
Note: This table reports the IHS transformed means of intermediate input purchases across the two groups from 2006 to 2016. Rest of the world represents the regions except Latin America, the OECD and the EU countries. SD denotes the standard deviations. Sourcing strategies and imports from low-income countries are provided in IHS transformed values.

Figure 2.1 plots the distribution of productivity levels, capital investments and intermediate consumption for robot adopters and non-adopters. We exploit two firm-level productivity measures from our data: the natural log of the firm's sales and labor productivity defined as the natural logarithm of value-added per worker. The distribution of adopters is evidently positioned to the right of non-adopting firms in each plot. The top panel indicates that robot adopting firms are on average more productive whereas the bottom of the panel depicts that adopters invest in capital more (on the left side) and have higher intermediate consumption (on the right side). The differences between the two groups are also consistent with the model that robot adopters have higher productivity $A > \tilde{A}$, $Y^{\mathbb{1}_R} > Y$,[12] and higher capital investments, $f^R > 0$, than non-adopters. Table A2 in Appendix 2.A.1 provides additional descriptive statistics showing similar patterns.

If firms continued sourcing intermediate inputs from suppliers after adopting robots, then their intermediate input purchases must have increased because robots increases productivity and larger amount of producing final goods requires larger amount of intermediate input usage. This mechanism relies on the assumption that the final output is obtained using two composite inputs: $Y^{\mathbb{1}_R} = (X^s)^{\beta}(X^{\mathbb{1}_R})^{1-\beta}$. To see the empirical validity of it, we regress each sourc-

[12]Also in Equation (2.7), we show that for adopting robots, firm revenues must increase more than the costs to make the adoption more profitable.

Figure 2.1: Patterns of Adoption



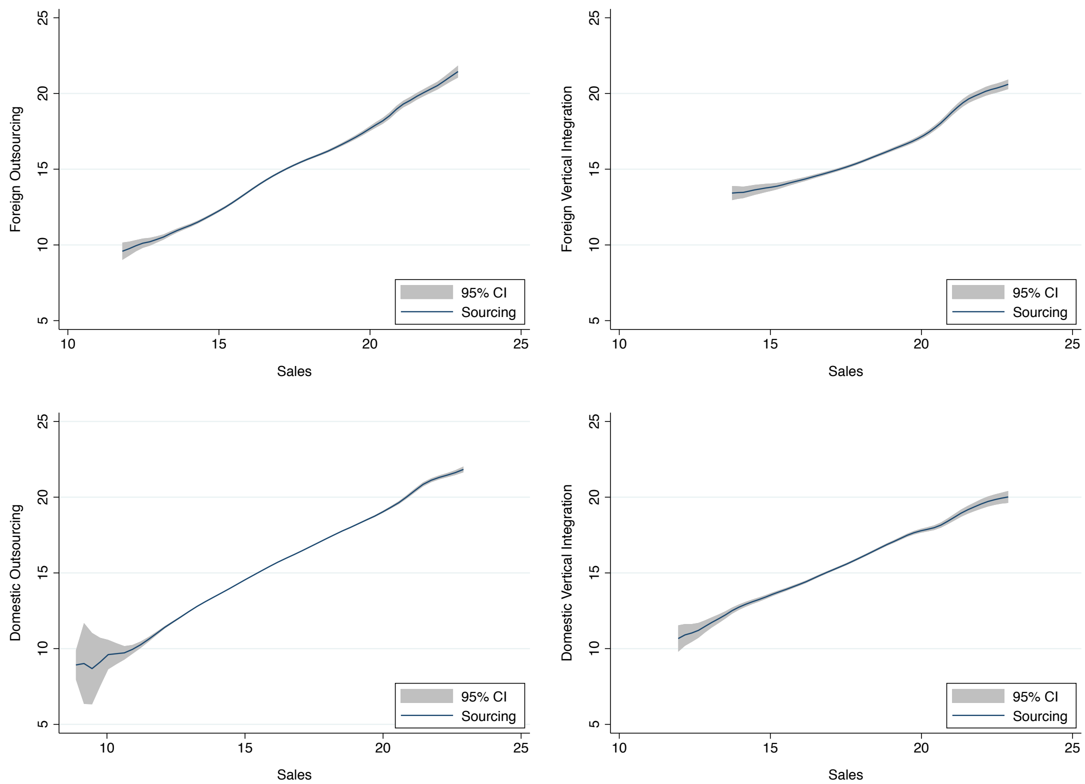
Note: This figure presents the distribution of productivity (measured as log sales), labor productivity (measured as log value added per worker), log capital investments and log intermediate consumption. The bold lines show the distributions of robot adopting firms and the dashed lines show the distributions of non-adopting firms.

ing activity (foreign outsourcing, foreign vertical integration, domestic outsourcing and domestic vertical integration) on sales. Figure 2.2 quantifies the differences in various sourcing strategies with 95 percent confidence intervals of local polynomial regressions. Intermediate input purchases for each type of sourcing strategy are larger in higher sales.[13] All panels depict a positive, monotonic and a strongly increasing relationship between sales and sourcing activities. Figure A9 in Appendix 2.A.2 shows similar patterns for the imports from Latin America and the rest of the world. Additionally, Figure A10 and Figure A11 present this relationship

[13] This is consistent with the patterns Antras et al. (2017) discovered that firms with higher sales source their intermediate inputs from a larger number of markets.

separately for adopters and non-adopters across sourcing strategies.

Figure 2.2: Sales and Intermediate Input Purchases of Sourcing Firms

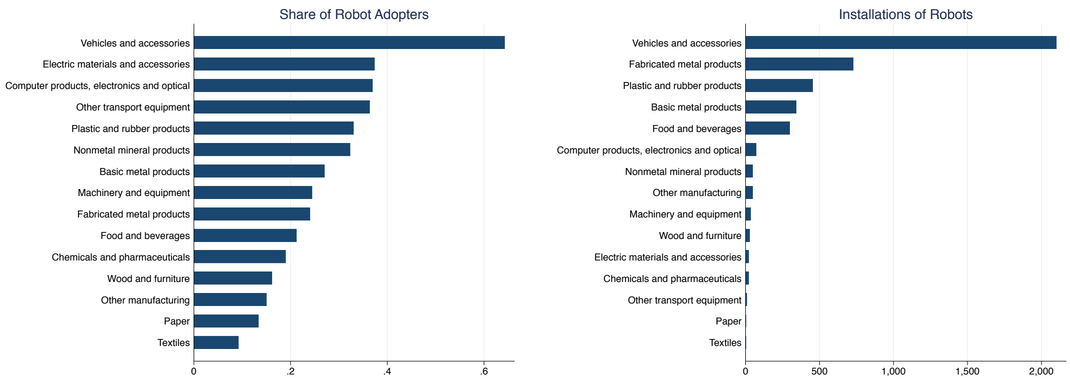


Note: Figures present the smoothed values with confidence bands from local polynomial regressions of intermediate input sourcing (measured as IHS values of each sourcing activity) on firm productivity (measured as log sales). Firms that were not involved in a sourcing strategy in a given year are excluded from the estimations.

Finally, Figure 2.3 shows the variability of adopters and robots across industries. The left panel depicts the share of adopters and the right panel shows the average installations of robots in each industry. Vehicles and accessories has the highest share of adopters, almost 80% of the firms, and it is most intensely robotized industry, followed by Fabricated metal products, Plastics and rubber products, Basic metal products and Food and beverages. The remaining industries employ relatively much less robots and have lower share of adopters.

The facts documented in this section point to substantial differences between robot adopters and non-adopters. The empirical analysis conducted in the next

Figure 2.3: Robot Adopters by Industry



Note: The figure presents the adoption patterns across industries. The left panel displays the share of robot adopting firms by industry and the right panel displays the installations of robots on average in each industry.

section explores the dynamics of the relationship between robot adoption and sourcing activities in greater detail.

2.5 Empirical Analysis

In this section, we empirically investigate how robot adoption affected firms' sourcing strategies and imports from low-income countries. In Section 2.5.1, we describe the details of our identification strategy and discuss possible threats to identification. In Section 2.5.2, we present the results of our estimations and test the robustness of our findings.

2.5.1 Identification Strategy

In our empirical specification, we relate time varying sourcing activities of firms to their robot adoption decisions. Potential endogeneity concern is that firm level shocks to demand and productivity may affect both robot adoption decision and firm-level sourcing activity. To address this concern, we need an instrument that is correlated with firm-year robot adoption probability but orthogonal to changes in the firm's productivity and sourcing activity.

Our instrumental variable strategy specifies that firm's robot adoption decision is driven by technological progress in robotics. Adoption probability of firm i in industry j in period t is instrumented by interacting a firm specific pre-sample imported technology share in year 2005 in industry j with robot adoption trends of industry j in other countries. Similar to the approach used by Acemoglu and Restrepo (2020), we use annual industry-level robot installations in four other European Union countries (Germany, France, Italy and the UK) to reflect robot adoption trends.[14] We choose countries displaying similar robot adoption patterns and sectoral structures (e.g. Krenz et al., 2021). Figure A12 in Appendix 2.A.2 shows the trends in the stock of robots in each country over this period and confirms our expectation that it may serve as a technological frontier. We additionally use robot installations in Scandinavian countries for the construction of our alternative instrument to test the robustness of our results.[15] Our instrument is defined as follows:

$$z_{ijt} = \ln\left(\frac{I^T_{ij2005}}{I^T_{j2005}} \times \sum_{c=1}^{4} Robots_{cjt}\right). \tag{2.10}$$

$Robots_{cjt}$ denotes industry-level new installations of robots in country c in period t and the data are constructed from the IFR dataset. I^T_{ij2005} and I^T_{j2005} represent pre-sample technology imports of firm i and industry j in 2005, respectively.

Notice that the shocks arising from our instrument must be exogenous to the firm and they vary across firms over time. $Robots_{jt}$ captures the changes in industry-level robot adoption trends driven by technological advancements in robotics industry. Worldwide technological advances in robotics and robot adoption trends outside of Spain are arguably exogenous shocks to Spanish firms.

A concern for our instrument may arise if an adopting firm exports robots to the EU countries.[16] The exogeneity condition of robot adoption trends of industry j in other countries would then be violated if changes in *Robots* are driven by robot supply shock from Spanish firm i, though odds are presumably

[14] This strategy was primarily used by Autor et al. (2013) and Bloom et al. (2016) in trade literature to account for import competition due to the supply shocks from China.

[15] Note that Scandinavian countries in our alternative instrument have substantially smaller population compared to Spain.

[16] For instance, a Spanish robot producer may have been producing substantial amount of robots and reducing the price of robots, facilitating the adoption of other countries.

against such a possibility. Spain is not a major robot producer country and therefore Spanish firms very likely import robots from high-income countries such as Japan and Germany. On the other hand, a robot is not an intermediate input that firm i may import, i.e. dependent variable may not affect our instrument and induce reverse causality. Thus, these concerns are unlikely to pose a threat to our identification strategy.

Initial shares I^T_{ij2005}/I^T_{j2005} measure the firm-level differential exogenous exposure to the industry-level common shocks. Firm i might have imported technology because of a business relationship in the past with some technology exporters abroad set in pre-sample period, which would probably be consistent over time. Or, technology that firm i imports may be particularly crucial for the production of the products firm i produces. Pre-sample data on imported technology allows us to prevent firm-level technological change that may affect input demand across years. In our setting, firm i's exposure to industry-level robot adoption trends increases with imported technology in the pre-sample period.

To present our baseline results, we estimate the following equation:

$$\ln I^{s,l}_{ijt} = \beta R_{ijt} + \varphi_{jt} + \varepsilon_{ijt}, \tag{2.11}$$

where $I^{s,l}_{ijt}$ denotes the IHS transformed values of intermediate input purchases for sourcing, s indexes the sourcing strategy and l indexes the location of the supplier. We use IHS (inverse hyperbolic sine) transformation of all the outcome variables (sourcing activities and imports from the Rest of the World and Latin America) to preserve the observations with zero values in the sample, which would otherwise be undefined in standard logarithmic form and dropped out of the analysis.[17] R_{ijt} is a dummy variable we instrument for and it takes the value 1 if firm i is robot user in period t and 0 otherwise. φ_{jt} denotes industry-year fixed effects absorbing the time varying shocks to adoption at the industry-level. ε_{ijt} is the error term.

According to our theoretical framework, we expect the parameter β to be positive after adopting robots if the firm continues sourcing. Adoption of robots boosts productivity and the firm needs more inputs to produce larger amount of

[17] IHS is defined as $\ln(x + \sqrt{x^2+1})$ and it behaves similar to log. However, another common approach to deal with such circumstances is to insert one to each value in the sample before taking logs of them. Conclusions are the same but the results only slightly differ when the variables are treated as such.

output. Thus, if $\beta < 0$ would indicate that robot adoption induced a decline in intermediate input purchases from low-income countries, i.e. reshoring the production of some inputs back to home country.[18] In estimation of the true impact of robot adoption conditional on controls, first reason that the firm may increase sourcing inputs after robot adoption is that the firm may substitute foreign inputs with domestic inputs. Since our dataset allows us to distinguish foreign and domestic inputs, we rule out this possibility by controlling for domestic sourcing activities (foreign sourcing activities) when estimating the effects on foreign sourcing activities (domestic sourcing activities). Moreover, the firm may substitute inputs purchased from suppliers for the inputs previously produced within the firm, i.e. starting to source inputs from suppliers. To address this possibility, we control for the lagged sourcing activity that can accurately capture the persistence of sourcing activities.[19] Considering these concerns, we estimate the following equation:

$$\ln I_{ijt}^{s,l} = \beta_1^{'} R_{ijt} + \beta_2^{'} \ln I_{ijt-1}^{s,l} + \beta_3^{'} \ln I_{ijt}^{s,l^-} + \beta_4^{'} \ln I_{ijt}^{s^-,l^-} + \varphi_{jt} + \varepsilon_{ijt}^{'} \tag{2.12}$$

where $I_{ijt-1}^{s,l}$ denotes the lagged sourcing activity. s^- and l^- represent the sourcing strategy and the location other than the estimated one: outsourcing if vertical integration is dependent variable and domestic sourcing strategy if foreign sourcing strategy is dependent variable, and vice versa. For instance, $I_{ijt}^{s^-,l^-}$ is domestic vertical integration if dependent variable $I_{ijt}^{s,l}$ is foreign outsourcing.

Second reason of a change in sourcing activities after robot adoption may be due to a productivity shock. For instance, robot installations in developed countries and sourcing activity of firm i may be correlated because an export supply shock from low-income countries (or time-varying demand shocks of inputs from high-income countries) may decrease (increase) input price and foster robot adoption trends in developed countries.[20] Similarly, $Robots_{jt}$ may be correlated

[18]In fact, robots may replace *some* tasks performed by suppliers' workers and continue importing other inputs produced by tasks not yet substituted by robots of sourcing firm. If sourcing firm increases it's productivity after robot adoption, even if robots replace some tasks, we may find an increase in sourcing activity after robot adoption.

[19]As shown by recent studies using the same dataset, robot adoption may encourage firms to enter into import markets (e.g. Stapleton and Webb, 2020; Alguacil et al., 2022).

[20]$Robots_{jt}$ may increase for two reasons in this scenario. First, firms in developed countries receive lower input prices as a productivity shock which then facilitates their

with $I_{ijt}^{s,l}$ if increasing robot installations in Germany affects the production of suppliers in low-income countries.[21] To deal with this issues, we incorporate the log of firm-year input price index and industry by time fixed effects to control for time varying shocks to demand. Recall that firms' potential reshoring decisions are also motivated by rising labor costs in emerging markets, beyond other factors. By controlling for the input price index, we also account for the fact that increased imported input costs may incentivize a firm to use robots and reduce its purchases of intermediate inputs.

A trade shock can increase new sourcing opportunities for firms (e.g. Bernard et al., 2020). Import or export tariff changes in Spain are set at the EU level and therefore plausibly exogenous to individual Spanish firms. However, the expansion of sales to new export markets may encourage the firm to invest in productivity enhancing technologies or allow them to bear fixed cost of technology investments more easily (e.g. Lileeva and Trefler, 2010; Bustos, 2011). We include the log of the number of markets as an adequate measure to control for the changes at the extensive margin and export intensity defined as exports to sales ratio to control for demand shocks outside of Spain at the intensive margin.[22]

Another potential threat to our identification strategy is that a firm specific shock changing the input demand of firm i, $I_{ijt}^{s,l}$, may affect *Robots*. *Robots* may be correlated with the sourcing activity of the firm if the firm is sourcing inputs from Germany, Italy, France or the UK instead of low and middle-income countries.[23] This is unlikely the case since Germany, Italy, France or the UK are not the countries that a Spanish firm may be involved in sourcing inputs to to take advantage of lower labor costs. Still, to deal with this issue, we estimate our model using imports from low and middle income countries defined as Latin America and the Rest of the World in our dataset which includes countries except OECD and the

robot adoption decision. Second, robot producers using inputs from low-income countries may increase the supply of robots, therefore reduce robot prices and encourage robot users to employ more robots.

[21]We thank a reviewer for pointing out this possibility.

[22]Our choice of export intensity exploits how the firm performs in foreign markets particularly rather than overall performance in terms of sales.

[23]This may be due to the fact that firm i's higher demand for inputs can encourage firms in these countries to use more robots to increase input supply. Another possibility is that increased number of robots in these countries may lead to an input supply shock to firm i in Spain.

EU.[24]

We also include the log of average wage of the firm in the estimations. Since our wage variable captures all compensations to workers in the firm, we use skill intensity instead of total employment to avoid a potential bias between these variables while controlling for any quality related changes. Finally, our estimation takes the form of the following equation:

$$\begin{aligned}\ln I^{s,l}_{ijt} = \beta^*_1 R_{ijt} + \beta^*_2 \ln I^{s,l}_{ijt-1} + \beta^*_3 \ln I^{s,l^-}_{ijt} + \beta^*_4 \ln I^{s^-,l^-}_{ijt} + \beta^*_5 \ln P^M_{ijt} \\ + \beta^*_6 \ln M_{ijt} + \beta^*_7 \tilde{X}_{ijt} + \beta^*_8 \ln W_{ijt} + \beta^*_9 \tilde{H}_{ijt} + \varphi_{jt} + \varepsilon^*_{ijt},\end{aligned} \tag{2.13}$$

where P^M_{ijt} is materials price index and M_{ijt} is the number of markets the firm is related to. X_{ijt}, S_{ijt} and $\tilde{X}_{ijt} = \frac{X_{ijt}}{S_{ijt}}$ denote firm i's exports, sales and export intensity, respectively. W_{ijt} denotes the average wage of the firm and $\tilde{H}_{ijt} = \frac{H_{ijt}}{H_{ijt}+L_{ijt}}$ represents the skill-intensity of the firm.

2.5.2 Results

This section presents the results of our estimations. We test the robustness of our estimations via an alternative instrument in the Appendix.

Table 2.3 reports results from estimating Equation (2.11) for sourcing strategies. Our baseline specification only includes industry-year and region fixed effects. The first column in each panel presents the first-stage results and the second column in each panel presents the corresponding 2SLS estimates. The first-stage Kleibergen-Paap F-statistic for the instrument is above 20 in each panel and statistically significant at the 1% level, reported in columns 1, 3, 5 and 7. The coefficients on the instrument are positive as expected because a firm with the higher share of technology imports in an industry would be more exposed to global technological developments. A strong positive correlation between the instrument and robot adoption probability in the first-stage estimates suggests that it is very unlikely that our estimates are biased by weak instruments. The 2SLS estimates in columns 2, 4, 6 and 8 depict a large and statistically significant relationships

[24]Even if the firm imports inputs from low-income countries, $I^{s,l}_{ijt}$ may be correlated with *Robots* if the firm is capable of generating a supply shock in low-income countries that can change the demand for robots in high-income countries. However, we disregard this scenario because of its implausibility since a Spanish firm is unlikely to generate a supply shock in input markets of low-income countries.

Table 2.3: Baseline Results with Sourcing Strategies

	Foreign Outsourcing		Foreign Vertical Integration		Domestic Outsourcing		Domestic Vertical Integration	
	1st Stage (1)	2SLS (2)	1st Stage (3)	2SLS (4)	1st Stage (5)	2SLS (6)	1st Stage (7)	2SLS (8)
Robot adoption		17.87***		25.57***		7.342***		2.021
		(3.639)		(5.920)		(1.595)		(3.111)
Instrument	0.0552***		0.0552***		0.0555***		0.0555***	
	(0.0121)		(0.0121)		(0.0121)		(0.0121)	
Observations	9324	9324	9322	9322	9345	9345	9347	9347
Year $\times$ Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	20.9		20.7		20.9		20.9	

Notes: This table presents the effects of robots on sourcing strategies. The estimations show the baseline results without any set of controls. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

between sourcing strategies and robot adoption. The estimated coefficients on foreign outsourcing, foreign vertical integration and domestic outsourcing are respectively 17.87, 25.57 and 7.34 log points and statistically significant at the 1% level. However, we find no impact of robot adoption on domestic vertical integration as the estimated coefficient reported in column 8 is small and statistically insignificant.

Table 2.4: Baseline Results with Destinations

	Rest of the World		Latin America	
	1st Stage (1)	2SLS (2)	1st Stage (3)	2SLS (4)
Robot adoption		11.48***		6.921***
		(2.585)		(2.309)
Instrument	0.0617***		0.0561***	
	(0.00999)		(0.0107)	
Observations	20016	20016	13739	13739
Year × Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	38.2		27.5	

Notes: This table presents the effects of robots on imports from two locations. The estimations show the baseline results without any set of controls. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

In Table 2.4, we present estimates for specifications in which the dependent variable is imports from low-income countries. Similar to the estimates for sourcing strategies, the first-stage results in columns 1 and 3 demonstrate a strong and significant relationship between the instrument and robot adoption with sufficiently high Kleibergen-Paap F-statistics. Columns 2 and 4 report the corresponding 2SLS estimates of the relationship between robot adoption and imports from low-income countries. The coefficient estimates of these specifications are large and statistically significant at the 1% level.

Notice however that substantially high magnitudes of these estimates point to the possibility of an upward bias due to unobserved shocks as we discussed in the previous section. In order to evaluate the robustness of our estimates to concern

Table 2.5: Robot Adoption and Selection into Sourcing Strategies

	Foreign Outsourcing		Foreign Vertical Integration		Domestic Outsourcing		Domestic Vertical Integration	
	1st Stage (1)	2SLS (2)	1st Stage (3)	2SLS (4)	1st Stage (5)	2SLS (6)	1st Stage (7)	2SLS (8)
Robot adoption		7.177***		6.030***		2.152		-1.268
		(2.277)		(2.328)		(1.476)		(1.241)
Instrument	0.0380***		0.0378***		0.0306***		0.0368***	
	(0.0111)		(0.0123)		(0.0114)		(0.0115)	
Lag foreign outsourcing	0.0107***	0.638***						
	(0.00143)	(0.0312)						
Lag foreign vertical integration			0.00606**	0.767***				
			(0.00238)	(0.0298)				
Lag domestic outsourcing					0.0136***	0.598***		
					(0.00208)	(0.0307)		
Lag domestic vertical integration							0.0121***	0.863***
							(0.00204)	(0.0182)
Foreign Outsourcing					0.0114***	0.0398**	0.0125***	0.0303*
					(0.00151)	(0.0182)	(0.00156)	(0.0173)
Foreign Vertical Integration					0.00507**	0.0103	0.00299	0.0312**
					(0.00242)	(0.0140)	(0.00242)	(0.0126)
Domestic Outsourcing	0.0126***	0.0391	0.0161***	-0.0744*				
	(0.00211)	(0.0369)	(0.00223)	(0.0414)				
Domestic Vertical Integration	0.0118***	-0.0395	0.0125***	-0.0333				
	(0.00202)	(0.0307)	(0.00205)	(0.0318)				
Observations	7948	7948	7946	7946	7956	7956	7957	7957
Year × Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	11.8		9.5		7.2		10.3	

Notes: This table presents the effects of robots on sourcing strategies. We include a set of variables in the estimations to control for selection into sourcing. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

over the substitution between foreign and domestically produced inputs, we include additional covariates and estimate Equation (2.12). The results presented in Table 2.5 show that our findings are robust to changes in sourcing strategies. Specifications for foreign outsourcing and foreign vertical integration deliver statistically significant estimates at the 1% level. As shown in columns 2 and 4, the estimated coefficients are smaller in magnitude than in our baseline results but remain large. The estimated coefficient on domestic outsourcing remains positive, although it is no longer significant while the coefficient on domestic vertical integration turns to negative and remains statistically insignificant. Lagged sourcing activities are statistically significant at the 1% level in each specification, indicating an important role of persistence in sourcing activities. Conditional on sourcing activity in the previous period and the changes in any switching between foreign and domestic sourcing, we find that robot adoption increases foreign outsourcing by 7.177 log points and foreign vertical integration by 6.030 log points.

In Table 2.6, we use imports from low-income countries as dependent variables and present results from estimating Equation (2.12). The magnitude of estimated coefficient on imports from the Rest of the World drops to 2.425 log points and remains significant at the 1% level. The coefficient estimate on Latin America is still positive, but close to zero, and becomes statistically insignificant. As in sourcing strategies, lagged sourcing activities seem to play an important role in our estimations as the coefficients we obtain are notably high and significant at the 1% level, implying a location persistence in importing. The results also indicate that imports from two geographies do not substitute each other since the coefficient estimates are positive (0.0578 for the Rest of the World shown in column 4 and 0.206 for Latin America shown in column 2) and statistically significant at the 1% level.[25]

A productivity shock may threaten the validity of our identification strategy if the shock is correlated with robot adoption and sourcing activity and threaten the validity of our identification strategy. We estimate Equation (2.13) and assess the robustness of the baseline results to inclusion of the full set of controls that we motivated and described in the previous section. When we condition on productivity shocks, the 2SLS estimates reported in Table 2.7 are qualitatively similar compared to previous results. Most importantly, the effects on foreign sourcing

[25]If imports from two locations were substitutes, we would have found the coefficients with negative signs, e.g. an increase in imports from Latin America would reduce imports from the Rest of the World.

Table 2.6: Robot Adoption and Selection into Importing from Developing Countries

	Rest of the World		Latin America	
	1st Stage (1)	2SLS (2)	1st Stage (3)	2SLS (4)
Robot adoption		2.425***		0.386
		(0.765)		(0.471)
Instrument	0.0494***		0.0471***	
	(0.0107)		(0.0109)	
Lag imports (Rest of the World)	0.0109***	0.819***		
	(0.00176)	(0.0138)		
Lag imports (Latin America)			-0.00186	0.840***
			(0.00322)	(0.0129)
Imports (Rest of the World)			0.0114***	0.0578***
			(0.00183)	(0.00876)
Imports (Latin America)	-0.00175	0.206***		
	(0.00317)	(0.0156)		
Observations	12991	12991	12210	12210
Year $\times$ Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	21.3		18.7	

Notes: This table presents the effects of robots on imports from two locations. We include a set of variables in the estimations to control for selection into sourcing. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

strategies remain positive and significant. The coefficient estimates on foreign outsourcing and foreign vertical integration are 5.962 and 6.893, both statistically significant at the 5% level. The coefficients on domestic outsourcing is positive and the coefficient on domestic vertical integration is negative but both are statistically insignificant. The first-stage estimates become weaker than in baseline specifications. F-statistics are within the range of 4.1-6.4 but the instrument remains statistically significant at the 5% level for each sourcing strategy.

The results reported in Table 2.7 present that firm-level price index has a negative and significant relationship with domestic sourcing strategies, indicating that firms have been responsive to price changes in cases of domestic sourcing while the effects on foreign sourcing strategies are insignificant. The coefficient on

Table 2.7: Impact of Robot Adoption on Sourcing Strategies

	Foreign Outsourcing		Foreign Vertical Integration		Domestic Outsourcing		Domestic Vertical Integration	
	1st Stage (1)	2SLS (2)	1st Stage (3)	2SLS (4)	1st Stage (5)	2SLS (6)	1st Stage (7)	2SLS (8)
Robot adoption		5.962**		6.893**		1.283		-2.200
		(2.706)		(3.359)		(1.727)		(1.857)
Instrument	0.0292**		0.0290**		0.0239**		0.0288**	
	(0.0115)		(0.0126)		(0.0119)		(0.0120)	
Lag foreign outsourcing	0.00823***	0.638***						
	(0.00143)	(0.0288)						
Lag foreign vertical integration			0.00306	0.777***				
			(0.00247)	(0.0288)				
Lag domestic outsourcing					0.0107***	0.603***		
					(0.00204)	(0.0295)		
Lag domestic vertical integration							0.0105***	0.861***
							(0.00201)	(0.0220)
Foreign Outsourcing					0.00871***	0.0405**	0.00934***	0.0290
					(0.00151)	(0.0164)	(0.00155)	(0.0191)
Foreign Vertical Integration					0.00260	0.00288	0.000826	0.0203
					(0.00249)	(0.0108)	(0.00247)	(0.0128)
Domestic Outsourcing	0.00981***	0.0451	0.0119***	-0.0719				
	(0.00207)	(0.0336)	(0.00214)	(0.0444)				
Domestic Vertical Integration	0.0102***	-0.0264	0.0107***	-0.0376				
	(0.00199)	(0.0298)	(0.00203)	(0.0383)				
Materials price index	-0.0246	0.339	-0.0167	-0.0272	-0.0358	-0.339**	-0.0322	-0.247*
	(0.0364)	(0.281)	(0.0366)	(0.274)	(0.0367)	(0.154)	(0.0361)	(0.139)
Markets	-0.000336	0.558***	0.0116	-0.0221	-0.00381	0.124	0.00271	0.0399
	(0.0204)	(0.155)	(0.0209)	(0.164)	(0.0206)	(0.0791)	(0.0204)	(0.0895)
Export intensity	0.140**	0.169	0.159***	-0.935	0.138**	0.0382	0.144**	0.112
	(0.0551)	(0.602)	(0.0560)	(0.755)	(0.0557)	(0.309)	(0.0558)	(0.350)
Wage	0.167***	-0.0194	0.186***	-0.865	0.196***	0.681*	0.190***	1.179***
	(0.0351)	(0.549)	(0.0360)	(0.682)	(0.0352)	(0.396)	(0.0355)	(0.398)
Skill-intensity	-0.117	0.206	-0.117	1.835*	-0.0735	0.566	-0.100	0.800
	(0.124)	(0.979)	(0.126)	(1.086)	(0.126)	(0.546)	(0.125)	(0.617)
Observations	7870	7870	7868	7868	7877	7877	7878	7878
Year $\times$ Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	6.4		5.3		4.1		5.8	

Notes: This table presents the effects of robots on sourcing strategies while including the full set of controls in the estimations. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table 2.8: Impact of Robot Adoption on Imports from Developing Countries

	Rest of the World		Latin America	
	1st Stage (1)	2SLS (2)	1st Stage (3)	2SLS (4)
Robot adoption		2.309**		0.559
		(1.155)		(0.737)
Instrument	0.0332***		0.0318***	
	(0.0108)		(0.0110)	
Lag imports (Rest of the World)	0.00640***	0.820***		
	(0.00173)	(0.0131)		
Lag imports (Latin America)			-0.00243	0.840***
			(0.00313)	(0.0133)
Imports (Rest of the World)			0.00707***	0.0584***
			(0.00182)	(0.00861)
Imports (Latin America)	-0.00209	0.201***		
	(0.00308)	(0.0158)		
Materials price index	-0.0688**	0.101	-0.0635*	0.119*
	(0.0344)	(0.150)	(0.0347)	(0.0687)
Markets	0.000475	0.185***	0.00239	0.0601
	(0.0181)	(0.0701)	(0.0185)	(0.0393)
Export intensity	0.192***	-0.0396	0.178***	-0.232
	(0.0510)	(0.301)	(0.0516)	(0.182)
Wage	0.226***	-0.222	0.230***	-0.188
	(0.0298)	(0.290)	(0.0302)	(0.175)
Skill-intensity	0.0456	-0.287	0.0441	0.108
	(0.124)	(0.428)	(0.125)	(0.228)
Observations	12881	12881	12105	12105
Year $\times$ Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	9.4		8.3	

Notes: This table presents the effects of robots on imports from two locations while including the full set of controls in the estimations. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

the log number of markets is positive and significantly correlated at the 1% level for foreign outsourcing. Moreover, the results suggest no relationship between the export intensity and sourcing activities. Hence, demand shocks outside of Spain do not affect sourcing strategies by no means and only foreign outsourcing is responsive to the changes at the extensive margin. We find that the firm-level wage is decreasing in the intensity of foreign sourcing but increasing in the intensity of domestic sourcing, however, statistically significant only for domestic sourcing strategies and the coefficient on skill-intensity is only significant at the 10% level for foreign vertical integration.

In Table 2.8, we report our findings from estimating Equation (2.13) using the Rest of the World and Latin America as dependent variables. With respect to the previous estimations presented in Table 2.6, the estimated coefficient on the Rest of the World drops slightly to 2.309 and remains significant at the 5% level. However, we find that the impact of robot adoption on Latin America is insignificant with a low magnitude. Overall, these results confirm that the impact of robot adoption on sourcing is robust to imports from low-income countries.

The estimates indicate that adopting robots increased sourcing with differential impacts across sourcing strategies in this sample. More specifically, we find that firms involved in foreign outsourcing and foreign vertical integration raised their sourcing activities in response to robot adoption. Our findings are robust to imports from low-income countries. These results are consistent with predictions from our theoretical framework that, conditional on the complementarity between robots and supplier's workers, adoption of robots induces higher input sourcing due to productivity increases from using robots. Since we find no evidence for a reduction in sourcing activities, the results in this paper imply that Spanish firms continued and increased sourcing rather than reshoring their intermediate input production.

2.6 Conclusion

In this paper, we use a detailed panel dataset of Spanish manufacturing firms to investigate how adopting robots affect outsourcing and vertically integrated firms' intermediate input purchases from both foreign and domestic suppliers. We find that robot adoption increased foreign sourcing activities and did not affect domestic sourcing activities from 2006 to 2016. These findings are robust to imports from low and middle-income countries.

We theoretically show that the probability of robot adoption is higher when adoption raises the revenue more than it raises costs and when the investment costs in robots are lower. According to our model, the reshoring decision is determined by the elasticity of substitution between the robots of the sourcing firm and offshore workers as well as the costs associated with bringing the production back to home country. Similar to previous studies, we observe in our data that robot adopting firms differ from non-adopting firms and the stylized facts we present are aligned with the assumptions and predictions in our theoretical framework.

Our dataset is limited to the information provided by Spanish sourcing firms in which we do not observe employment decisions of suppliers in other countries. Hence, this paper shows how the intermediate input trade between sourcing firms and suppliers have changed after sourcing firms adopted robots. However, it does not infer any direct conclusion about the effects on labor markets in offshore countries. Another caveat of the paper is that our sample is limited to the manufacturing sector. Considering the fact that robots are becoming increasingly more prevalent in services sectors, perhaps more research will be needed in the future to assess the effects of robots on offshore services.

The findings in this paper emphasize the long-term implications of technological developments on global sourcing. Our firm-level analysis shows that the new technologies may affect trade patterns differently depending on the organizational forms across distinct locations. An important question is to what extent our firm-level findings can be generalized to other countries in today's world economy with complex supply chains and specialization across countries. It remains a mystery yet how firms will organize their production globally in the future as sophisticated labor-saving technologies (e.g. 3D printing and AI) become more widely adapted in the production processes and whether the effects of robots will be parallel with the results presented in this paper.

2.A Appendices to Chapter 2

2.A.1 Appendix Tables

Table A1: Industry Matching ESEE-IFR

ESEE	IFR
12 - Basic metal products	24 - Basic metals 289 - Metal, unspecified 2931 - Metal (AutoParts)
9 - Chemicals and pharmaceuticals	19 - Pharmaceuticals, cosmetics 20-21 - other chemical products n.e.c. 229 - Chemical products, unspecified
15 - Computer products, electronics and optical	275 - Household/domestic appliances 262 - Computers and peripheral equipment 263 - Info communication equipment, domestic and prof. 265 - Medical, precision, optical instruments 279 - Electrical/electronics unspecified 2933 - Electrical/electronic (AutoParts) 26-27 - Electrical/electronics
16 - Electric materials and accessories	271 - Electrical machinery n.e.c. (non-automotive) 260 - Electronic components/devices 261 - Semiconductors, LCD, LED
13 - Fabricated metal products	25 - Metal products (non-automotive) 24-28 - Metal
14 - Machinery and equipment	28 - Industrial machinery
11 - Nonmetal mineral products	23 - Glass, ceramics, stone, mineral products (non-auto 2934 - Glass (AutoParts)
20 - Other manufacturing	91 - All other manufacturing branches
18 - Other transport equipment	30 - Other vehicles
10 - Plastic and rubber products	22 - Rubber and plastic products (non-automotive) 2932 - Rubber and plastic (AutoParts) 19-22 - Plastic and chemical products
17 - Vehicles and accessories	29 - Automotive 299 - Automotive unspecified 291 - Motor vehicles, engines and bodies 2999 - Unspecified AutoParts 2939 - Other (AutoParts)
7 - Paper 8 - Printing	17-18 - Paper
3 - Beverage 2 - Food and tobacco 1 - Meat products	10-12 - Food and beverages
5 - Leather, fur and footwear 4 - Textiles and clothing	13-15 - Textiles
6 - Timber 19 - Furniture	16 - Wood and furniture

Notes: The table shows the matching of industries between the ESEE dataset (on the left) and the IFR dataset (on the right). The classifications are provided along with the industry definitions.

Table A2: Descriptive Statistics

	Robot Adopters			Non-Adopters		
	Mean	SD	Obs.	Mean	SD	Obs.
Output	17.00	1.77	5113	15.28	1.71	12098
Sales	16.99	1.77	5113	15.26	1.72	12098
Value Added	15.71	1.64	5073	14.15	1.54	12003
Employment	4.89	1.37	4604	3.59	1.17	10843
Labor Productivity	3.95	0.62	5071	3.65	0.66	12003
Wage	10.50	0.32	4602	10.30	0.38	10837
Capital Investments	13.22	2.11	4402	11.47	2.22	8142
Skill Intensity	0.08	0.09	5446	0.06	0.09	13515
R&D Employment	12.39	87.48	5497	3.21	41.03	13558
Intermediate Consumption	16.61	1.89	5112	14.77	1.91	12093
Imports	14.91	2.41	4077	13.21	2.58	6615
Exports	15.70	2.46	4168	13.91	2.64	6957

Notes: This table reports the means, standard deviations and observations of some variables for robot adopting and non-adopting firms in the sample. Variables in the table span the period 2006-2016. Robot adopters represent the firms using robots in production for the given year whereas Non-adopters represent the firms not using robots in production for the given year. Output is the log of the sum of sales, the variation of stocks for sale and other current management income. Sales is the log of firms' product sales and value-added is the log of firms' value added on production. Employment is the log of average number of workers employed by the firm during the year. Labor productivity represents the log of value added per worker. Wage denotes the log of labor cost per employee. Capital investments is measured as the log of the sum of the purchases in capital goods. Skill intensity is the percentage of engineers and graduates within the total personnel. R&D employment represents the total number of employees engaged in R&D activities. Intermediate consumption is the log of the sum of purchases and external services, minus the variation in the stock of purchases. Imports is the log of value of imports and exports is the log of value of exports.

Table A3: Baseline Results with Sourcing Strategies (using alternative instrument)

	Foreign Outsourcing		Foreign Vertical Integration		Domestic Outsourcing		Domestic Vertical Integration	
	1st Stage	2SLS	1st Stage	2SLS	1st Stage	2SLS	1st Stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot adoption		15.10***		25.19***		5.625***		-1.757
		(4.951)		(8.490)		(2.165)		(5.295)
Alternative instrument	0.0507***		0.0506***		0.0508***		0.0508***	
	(0.0177)		(0.0178)		(0.0177)		(0.0177)	
Observations	9324	9324	9322	9322	9345	9345	9347	9347
Year × Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	8.2		8.1		8.2		8.2	

Notes: This table presents the effects of robots on sourcing strategies using an alternative instrument constructed from robot installations in Scandinavian countries (Denmark and Finland, Norway and Sweden). The estimations show the baseline results without any set of controls. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table A4: Baseline Results with Destinations (using alternative instrument)

	Rest of the World		Latin America	
	1st Stage	2SLS	1st Stage	2SLS
	(1)	(2)	(3)	(4)
Robot adoption		11.91***		6.829*
		(3.784)		(3.621)
Alternative instrument	0.0648***		0.0515***	
	(0.0152)		(0.0162)	
Observations	20016	20016	13739	13739
Year × Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	18.3		10.1	

Notes: This table presents the effects of robots on imports from two locations using an alternative instrument constructed from robot installations in Scandinavian countries (Denmark and Finland, Norway and Sweden). The estimations show the baseline results without any set of controls. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table A5: Robot Adoption and Selection into Sourcing Strategies (using alternative instrument)

	Foreign Outsourcing		Foreign Vertical Integration		Domestic Outsourcing		Domestic Vertical Integration	
	1st Stage (1)	2SLS (2)	1st Stage (3)	2SLS (4)	1st Stage (5)	2SLS (6)	1st Stage (7)	2SLS (8)
Robot adoption		6.028**		5.414*		2.134		-1.402
		(2.691)		(2.814)		(2.026)		(1.604)
Alternative instrument	0.0401***		0.0372**		0.0304**		0.0375**	
	(0.0150)		(0.0161)		(0.0147)		(0.0151)	
Lag foreign outsourcing	0.0112***	0.651***						
	(0.00142)	(0.0348)						
Lag foreign vertical integration			0.00775***	0.773***				
			(0.00231)	(0.0310)				
Lag domestic outsourcing					0.0139***	0.599***		
					(0.00207)	(0.0367)		
Lag domestic vertical integration							0.0121***	0.864***
							(0.00204)	(0.0214)
Foreign Outsourcing					0.0116***	0.0400*	0.0128***	0.0320
					(0.00152)	(0.0242)	(0.00156)	(0.0216)
Foreign Vertical Integration					0.00626***	0.0104	0.00443*	0.0319**
					(0.00235)	(0.0170)	(0.00237)	(0.0135)
Domestic Outsourcing	0.0130***	0.0544	0.0165***	-0.0641				
	(0.00211)	(0.0408)	(0.00223)	(0.0494)				
Domestic Vertical Integration	0.0119***	-0.0261	0.0124***	-0.0258				
	(0.00202)	(0.0337)	(0.00205)	(0.0373)				
Observations	7948	7948	7946	7946	7956	7956	7957	7957
Year × Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	7.2		5.4		4.3		6.2	

Notes: This table presents the effects of robots on sourcing strategies using an alternative instrument constructed from robot installations in Scandinavian countries (Denmark and Finland, Norway and Sweden). We include a set of variables in the estimations to control for selection into sourcing. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table A6: Robot Adoption and Selection into Importing from Developing Countries (using alternative instrument)

	Rest of the World		Latin America	
	1st Stage (1)	2SLS (2)	1st Stage (3)	2SLS (4)
Robot adoption		3.118** (1.319)		0.301 (0.740)
Alternative instrument	0.0452*** (0.0158)		0.0422*** (0.0160)	
Lag imports (Rest of the World)	0.0117*** (0.00177)	0.810*** (0.0191)		
Lag imports (Latin America)			-0.000994 (0.00321)	0.840*** (0.0129)
Imports (Rest of the World)			0.0122*** (0.00183)	0.0589*** (0.0117)
Imports (Latin America)	-0.000775 (0.00316)	0.206*** (0.0167)		
Observations	12991	12991	12210	12210
Year $\times$ Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	8.2		6.9	

Notes: This table presents the effects of robots on imports from two locations using an alternative instrument constructed from robot installations in Scandinavian countries (Denmark and Finland, Norway and Sweden). We include a set of variables in the estimations to control for selection into sourcing. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table A7: Impact of Robot Adoption on Sourcing Strategies (using alternative instrument)

	Foreign Outsourcing		Foreign Vertical Integration		Domestic Outsourcing		Domestic Vertical Integration	
	1st Stage (1)	2SLS (2)	1st Stage (3)	2SLS (4)	1st Stage (5)	2SLS (6)	1st Stage (7)	2SLS (8)
Robot adoption		4.441		6.188		1.584		-2.045
		(3.218)		(4.145)		(2.339)		(2.383)
Alternative instrument	0.0305*		0.0280*		0.0238		0.0290*	
	(0.0156)		(0.0166)		(0.0155)		(0.0158)	
Lag foreign outsourcing	0.00850***	0.652***						
	(0.00142)	(0.0319)						
Lag foreign vertical integration			0.00424*	0.781***				
			(0.00240)	(0.0294)				
Lag domestic outsourcing					0.0109***	0.600***		
					(0.00203)	(0.0344)		
Lag domestic vertical integration							0.0104***	0.860***
							(0.00201)	(0.0264)
Foreign Outsourcing					0.00880***	0.0378*	0.00948***	0.0275
					(0.00151)	(0.0214)	(0.00155)	(0.0237)
Foreign Vertical Integration					0.00345	0.00166	0.00186	0.0199
					(0.00242)	(0.0125)	(0.00242)	(0.0129)
Domestic Outsourcing	0.00999***	0.0604	0.0121***	-0.0633				
	(0.00206)	(0.0369)	(0.00214)	(0.0535)				
Domestic Vertical Integration	0.0102***	-0.0112	0.0106***	-0.0303				
	(0.00199)	(0.0334)	(0.00202)	(0.0460)				
Materials price index	-0.0266	0.294	-0.0175	-0.0406	-0.0365	-0.328*	-0.0333	-0.242*
	(0.0365)	(0.242)	(0.0367)	(0.254)	(0.0368)	(0.170)	(0.0362)	(0.144)
Markets	-0.000160	0.560***	0.0120	-0.0128	-0.00366	0.124	0.00293	0.0393
	(0.0205)	(0.136)	(0.0209)	(0.156)	(0.0206)	(0.0811)	(0.0204)	(0.0882)
Export intensity	0.148***	0.405	0.165***	-0.815	0.143***	-0.00629	0.150***	0.0881
	(0.0548)	(0.603)	(0.0560)	(0.844)	(0.0555)	(0.381)	(0.0557)	(0.419)
Wage	0.173***	0.253	0.191***	-0.728	0.200***	0.620	0.195***	1.149**
	(0.0351)	(0.619)	(0.0360)	(0.820)	(0.0352)	(0.510)	(0.0355)	(0.497)
Skill-intensity	-0.111	0.0127	-0.115	1.741	-0.0723	0.592	-0.0980	0.818
	(0.125)	(0.886)	(0.127)	(1.061)	(0.127)	(0.574)	(0.126)	(0.636)
Observations	7870	7870	7868	7868	7877	7877	7878	7878
Year × Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	3.8		2.9		2.4		3.4	

Notes: This table presents the effects of robots on sourcing strategies using an alternative instrument constructed from robot installations in Scandinavian countries (Denmark and Finland, Norway and Sweden) while including the full set of controls in the estimations. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

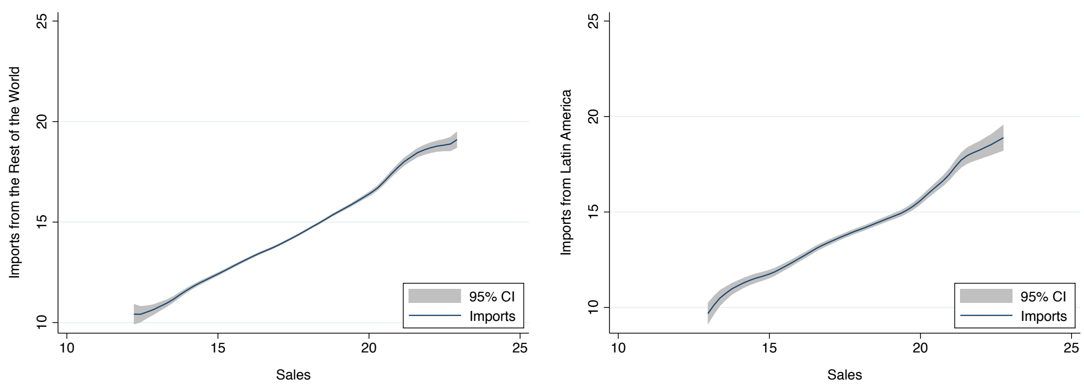
Table A8: Impact of Robot Adoption on Imports from Developing Countries (using alternative instrument)

	Rest of the World		Latin America	
	1st Stage (1)	2SLS (2)	1st Stage (3)	2SLS (4)
Robot adoption		3.397		0.329
		(2.175)		(1.150)
Alternative instrument	0.0295*		0.0277*	
	(0.0157)		(0.0159)	
Lag imports (Rest of the World)	0.00665***	0.813***		
	(0.00174)	(0.0185)		
Lag imports (Latin America)			-0.00190	0.839***
			(0.00314)	(0.0133)
Imports (Rest of the World)			0.00734***	0.0601***
			(0.00183)	(0.0112)
Imports (Latin America)	-0.00150	0.202***		
	(0.00309)	(0.0176)		
Materials price index	-0.0719**	0.182	-0.0664*	0.103
	(0.0345)	(0.220)	(0.0348)	(0.0907)
Markets	0.00107	0.184**	0.00280	0.0608
	(0.0181)	(0.0826)	(0.0185)	(0.0381)
Export intensity	0.201***	-0.266	0.187***	-0.187
	(0.0510)	(0.499)	(0.0516)	(0.254)
Wage	0.236***	-0.486	0.239***	-0.132
	(0.0298)	(0.534)	(0.0303)	(0.275)
Skill-intensity	0.0520	-0.330	0.0493	0.116
	(0.125)	(0.526)	(0.126)	(0.223)
Observations	12881	12881	12105	12105
Year $\times$ Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	3.5		3.0	

Notes: This table presents the effects of robots on imports from two locations using an alternative instrument constructed from robot installations in Scandinavian countries (Denmark and Finland, Norway and Sweden) while including the full set of controls in the estimations. Dependent variables are provided in IHS transformed values. Standard errors are clustered at the firm level reported in parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

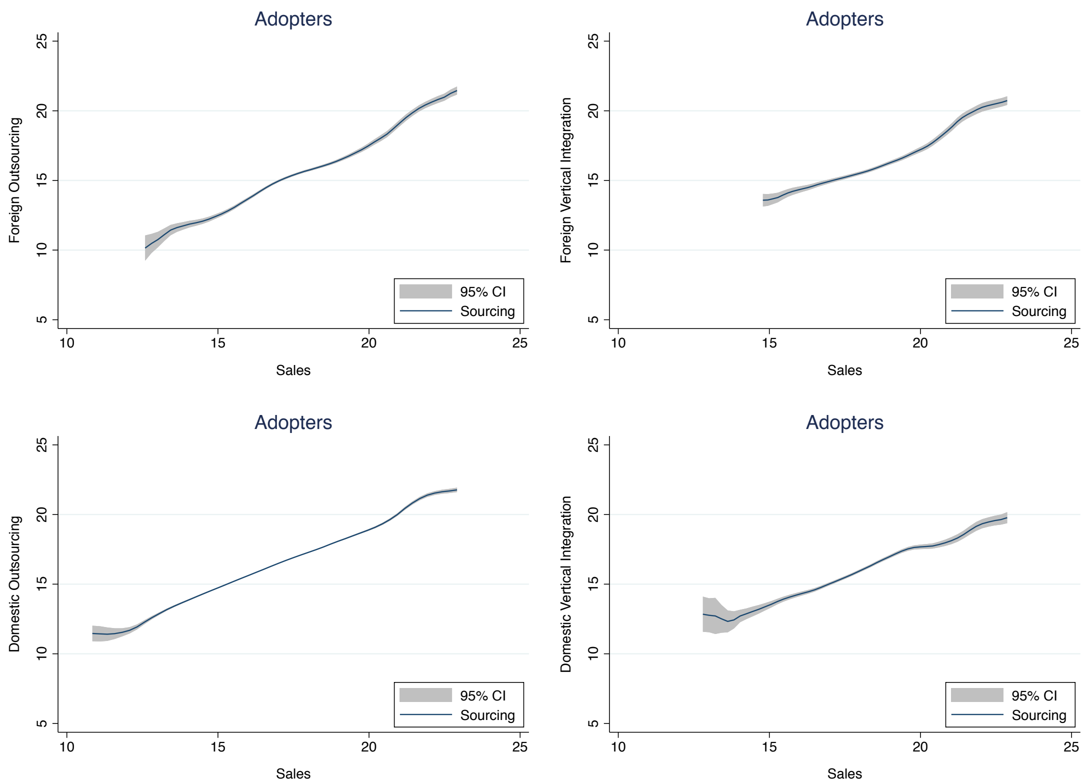
2.A.2 Appendix Figures

Figure A9: Sales and Intermediate Input Purchases of Sourcing Firms by Destinations



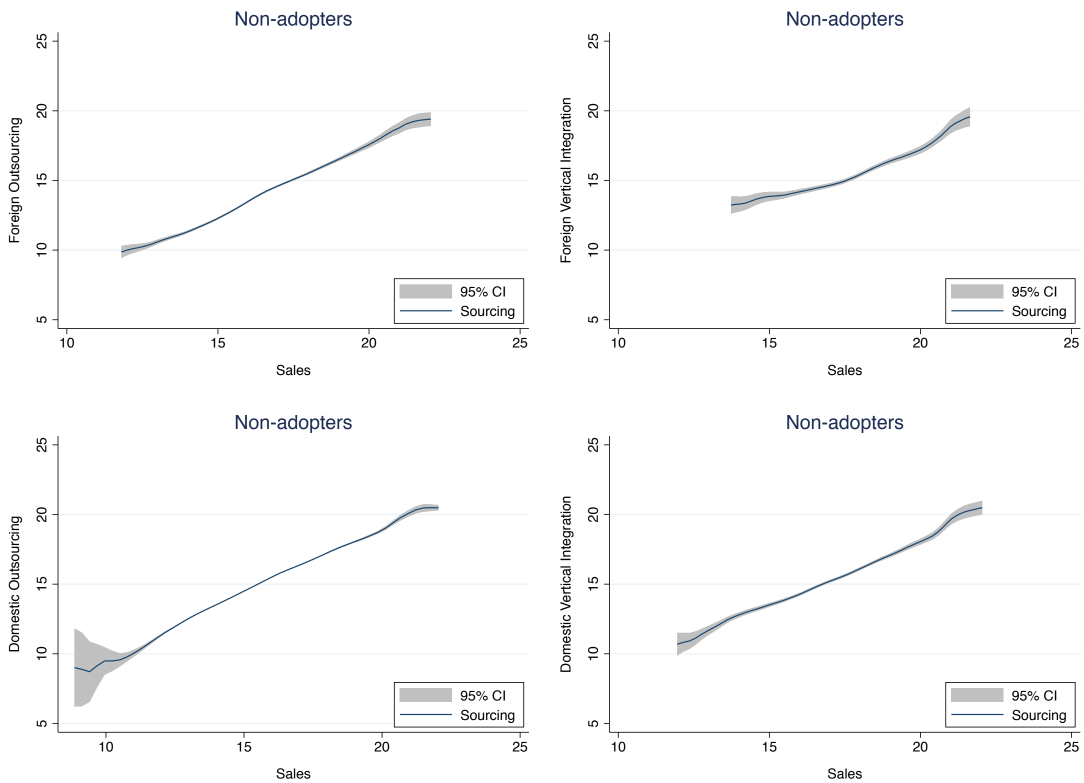
Note: Figures display the smoothed values with confidence bands from local polynomial regressions of IHS transformed imports from the Rest of the World (on the left panel) and from Latin America (on the right panel) on firm productivity (measured as log sales). Firms that did not import in a given year are excluded from the estimations.

Figure A10: Sales and Intermediate Input Purchases of Adopters



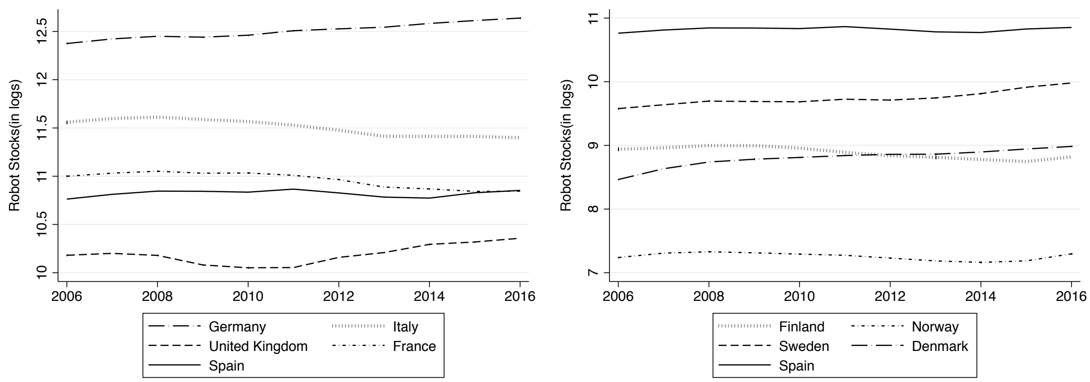
Note: Figures present the smoothed values with confidence bands from local polynomial regressions of intermediate input sourcing (measured as IHS values of each sourcing activity) on firm productivity (measured as log sales) for robot adopting firms. Firms that were not involved in a sourcing strategy in a given year are excluded from the estimations.

Figure A11: Sales and Intermediate Input Purchases of Non-adopters



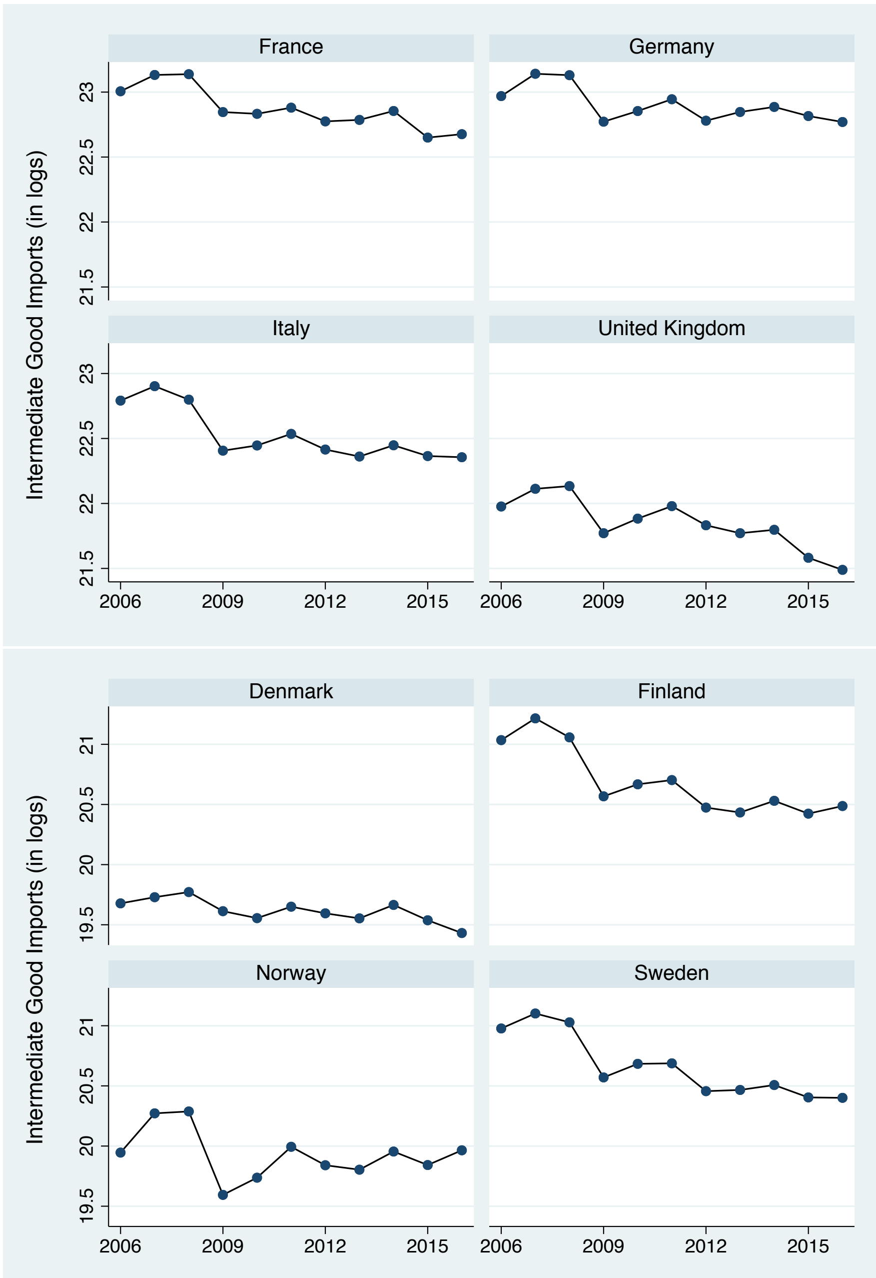
Note: Figures present the smoothed values with confidence bands from local polynomial regressions of intermediate input sourcing (measured as IHS values of each sourcing activity) on firm productivity (measured as log sales) for non-robot adopting firms. Firms that were not involved in a sourcing strategy in a given year are excluded from the estimations.

Figure A12: Robots in the EU Countries



Note: This figure presents the log stock of robots in the EU countries. The left panel compares the robot stocks in Germany, Italy, France and United Kingdom (the countries selected for our main instrument) with Spain. The right panel compares the robot stocks in Finland, Norway, Sweden and Denmark (the countries selected for our alternative instrument) with Spain.

Figure A13: Spain's Intermediate Good Imports



Note: This figure presents the trends in Spain's log intermediate good imports from the EU countries for 2006-2016.

2.A.3 Theory Appendix

The first-order condition of the problem in Equation (2.8) for $\mathbb{1}_R$ and X^s respectively yields

$$P^{Y^{\mathbb{1}_R}} Y^{\mathbb{1}_R} = \frac{(1-\mathbb{1}_S \nu) P^{X^s} \varphi^L X^{s\,1/\sigma}}{\beta} + \frac{\mathbb{1}_R f^R (1+\rho)}{\beta} \Big(\frac{\varphi^L + \varphi^R}{\varphi^R} \Big), \tag{2.14}$$

$$P^{Y^{\mathbb{1}_R}} Y^{\mathbb{1}_R} = \frac{(1-\mathbb{1}_S \nu) P^{X^s} \varphi^L X^{s\,1/\sigma}}{\beta \sigma}. \tag{2.15}$$

using above equations we can obtain

$$(1-\mathbb{1}_S \nu) P^{X^s} \varphi^L X^{s\,1/\sigma} \Big(\frac{1-\sigma}{\sigma} \Big) = \mathbb{1}_R f^R (1+\rho) \Big(\frac{\varphi^L + \varphi^R}{\varphi^R} \Big) \tag{2.16}$$

using Equation (2.2), we can express the previous equation as

$$P^{X^s} X^s (\varphi^L + \varphi^R)^{\left(\frac{1-\sigma}{\sigma}\right)\left(\frac{\sigma}{\sigma-1}\right)} = \mathbb{1}_R f^R (1+\rho) \Big(\frac{\varphi^L + \varphi^R}{\varphi^L \varphi^R} \Big) \Big(\frac{\sigma}{1-\sigma} \Big) \Big(\frac{1}{1-\mathbb{1}_S \nu} \Big) \tag{2.17}$$

By rearranging this expression, we can obtain the intermediate purchases of the firm from suppliers shown in Equation (2.9).

2.A.4 Variable Definitions

- Foreign outsourcing: percentage of intermediate imports from other (not related) firms in the same group (over total imports).
- Foreign vertical integration: percentage of intermediate imports from other firms in the same group (over total imports).
- Domestic outsourcing: percentage of intermediate purchases to other (not related) firms in Spain (over total sales).
- Domestic vertical integration: percentage of intermediate inputs purchased from related firms in Spain (over total sales).
- Concentration of suppliers: Percentage of the purchases of the company which come from its three biggest suppliers. We use this variable as a proxy for production fragmentation where lower concentration of suppliers indicates higher production fragmentation and vice versa.
- Imported technology: Payments for licenses and technical aid from abroad, in thousands of Euros. We use this variable as a proxy for dependency on foreign technology.
- Skill intensity: Percentage that engineers and graduates represent on the total personnel of the company on December 31st.
- Total purchases: It includes supplies of merchandise, raw materials and other supplies and the work carried out by other companies, excluding rappels and purchase returns. In euros.

Chapter 3

Export Destination and Firm Upgrading: Evidence from Spain

3.1 Introduction

One of the main established facts of trade literature is the superior performance of exporters to non-exporters but the causal direction of this relationship has been a particular subject of study. One explanation for this pattern is that exporters are ex-ante better performing firms even before entering export markets (e.g. Clerides et al., 1998; Bernard and Jensen, 1999). On the other hand, increased volume of exports due to larger market size encourages investments in new technologies which reduces the fixed costs per unit product and makes upgrading more profitable (e.g. Yeaple, 2005; Bustos, 2011). Another explanation is the learning-by-exporting mechanism which suggests that firms entering into export markets upgrade their technology and raise productivity through learning (e.g. Van Biesebroeck, 2005; De Loecker, 2007; Lileeva and Trefler, 2010; Bustos, 2011).

Market destination might play a role in explaining the impact of exporting on productivity because consumers in richer countries tend to have higher willingness to pay for high quality products. Previous studies documented that firms exporting to high-income countries produce higher quality products (e.g. Khandelwal, 2010; Crozet et al., 2012; Atkin et al., 2017), charge higher price for their products (e.g. Schott, 2004; Hummels and Klenow, 2005; Hallak, 2006; Bastos and Silva, 2010; Manova and Zhang, 2012; Bas and Strauss-Kahn, 2015) and use high quality input factors and technology (e.g. Brambilla et al., 2012; Kugler and Verhoogen, 2012; Hallak and Sivadasan, 2013; Bas and Strauss-Kahn, 2015; Bastos et al., 2018).[1] Firms may also improve their performance to compete in tougher markets by reducing marginal costs (e.g. Melitz and Ottaviano, 2008; Mayer et al., 2014; Aghion et al., 2018). On the other hand, customer's expectation of better product standards and qualities or customer's willing to share specific information might lead the exporter to increase quality. Finally, firms may be attracted to higher quality inputs from export markets or exposed to other firms/trainers/consultants.[2]

Does destination matter for firm-level upgrading and productivity improvements from exporting? This paper studies the changes in exports of Spanish manufacturing firms during the Great Recession to provide evidence on whether export destination is an important determinant of firms' upgrading efforts and productivity gains from exporting. I exploit the change in real effective exchange rate (REER) in Spain to isolate the causal effect of exporting to low- and high-income countries on firm productivity. Using devaluation in REER based on unit labor costs after 2008 to identify exogenous variation in exports across destinations (e.g. Verhoogen, 2008; Park et al., 2010; Brambilla et al., 2012; Bastos et al., 2018), I find differential effects on firms exporting to low-income and high-income destinations. In response to REER devaluation, firms exported to low-income destinations substantially increased their share of exports in sales but experienced a fall in productivity and reduced their attempts for upgrading activities. On the contrary, the share of exports to high-income countries in sales remained relatively stable and there has not been a significant impact on productivity and upgrading efforts during the period 2008-2012.

This paper is primarily related to the empirical literature that examines the role of export destination on firm-level outcomes. Previous literature has predominantly studied the firms exporting to countries with similar (e.g. Bustos, 2011; Lileeva and Trefler, 2010) or higher income level (e.g. Van Biesebroeck,

[1] Crozet et al. (2012) and Atkin et al. (2017) use directly observable dimensions of product quality. Using free on board prices that excludes transport costs and controlling for distance and other destination characteristics, Bastos and Silva (2010) show that firms charge higher prices for goods sold to richer markets. Manova and Zhang (2012), Martin (2012), Görg et al. (2017) provide similar findings for China, France and Hungary.

[2] Verhoogen (2021) surveys the related literature and explains various channels of firm upgrading.

2005; Atkin et al., 2017).[3] The analysis in this paper differs from and contributes to the literature by showing that export destination can be an important factor determining the relationship between exporting and firm performance.

This paper is most closely related to Park et al. (2010) who study how increased exports in China during the Asian financial crisis driven by currency depreciation increased firm performance. They find that larger exports to high-income destinations experienced productivity movements but their analysis includes only foreign owned firms.[4] However, empirical evidences suggest that foreign ownership induces productivity improvements and higher skill demand (e.g. Guadalupe et al., 2012; Koch and Smolka, 2019). Hence, I restrict the sample to domestically owned firms.

This paper is also related to the empirical literature that investigates productivity effects of exporting. One strand of the literature uses TFP as a measure of productivity gains but TFP measures may be erroneous particularly in the studies identifying the learning-by-exporting mechanism of exporting because TFP typically reflect the changes in markups, markdowns, product quality and product mix which would vary with exporting across destinations (e.g. De Loecker and Goldberg, 2014; Garcia-Marin and Voigtländer, 2019).[5] Other common measures used in the literature are spending on technology and innovation activities (e.g. Bustos, 2011; Lileeva and Trefler, 2010). This paper departs from these studies by using the data on direct upgrading activities. Particular advantage of this analysis is that it captures firms' efforts and attempts for upgrading in various ways without necessarily using technology investments or the outcomes of technology investments (e.g. innovation).

The rest of the paper is organized as follows. Section 3.2 presents the dataset used in the paper and provide a descriptive analysis. Section 3.3 introduces the empirical analysis and Section 3.4 reports the results. Section 3.5 concludes.

[3] One exception is De Loecker (2007) who reports that the TFP increases are lower for Slovenian firms exporting low-income countries.

[4] Supporting this hypothesis, De Loecker (2007) and Coelli et al. (2022) also find some evidence of smaller productivity gains and innovation activities for exporting to low-income countries than high-income countries.

[5] Estimating TFP typically relies on strong assumptions. Moreover, it may be considered as a determinant of subsequent upgrading rather than an outcome of upgrading efforts. See Verhoogen (2021) for discussions on various upgrading measures used in the literature.

3.2 Data and Context

In this section, I explain the details of the firm-level dataset and present the preliminary results of the descriptive analysis on the export performance of manufacturing firms during the Great Recession.

Firm-level data used in this paper come from the Encuesta Sobre Estrategias Empresariales (ESEE) provided by the SEPI foundation in Madrid. The ESEE survey is a representative panel data set for the Spanish manufacturing sector which provides substantial amount of information from around 2000 firms with 10 or more employees every year. It distinguishes between 20 different industries at the two-digit level of the NACE classification and 17 regions of NUTS2 classification. Additionally, industry-level price indices are obtained from the Spanish Statistical Office (Instituto Nacional de Estadistica, INE) and real effective exchange rate (REER) based on unit labor costs come from the IMF.

Obtaining directly observable measures of firm upgrading is often difficult. Some researchers use R&D expenditures, patents, total factor productivity (TFP), technology adoption and product choices while it is yet unclear which alternative most appropriately characterizes firm upgrading or attempts of upgrading.[6] In the sample, I observe whether firms involved in technological collaborations, attempted to learn new technologies, conducted innovative activities such as R&D and whether these efforts led to innovation related outcomes such as patents, product and process innovations. Hence, the dataset is unique as it includes direct measures of firm level information on upgrading efforts and innovation activities.

The data also incorporate information on the export destinations of firms and specify whether the export revenues are generated in the OECD countries, Latin American countries or the Rest of the World that typically represents low- and middle-income markets. In the analysis, I define the Rest of the World as low-income destination and OECD countries as high-income destination, which is in accordance with the World Bank country classification.[7] The main analysis

[6] Verhoogen (2021) provides a very detailed survey on this topic. Braguinsky et al. (2021) study the cotton spinning industry in early industrialization period in Japan. They compute firms' product upgrade trials as a measure of upgrading efforts.

[7] In contrast, several countries such as Chile (member since 2010), Turkiye (member since 1961) and Mexico (member since 1964) can arguably considered as middle-income countries. However, I rely on the World Bank classification in the analysis as Brambilla et al. (2012) that use the same classification in defining high-income and low-income countries.

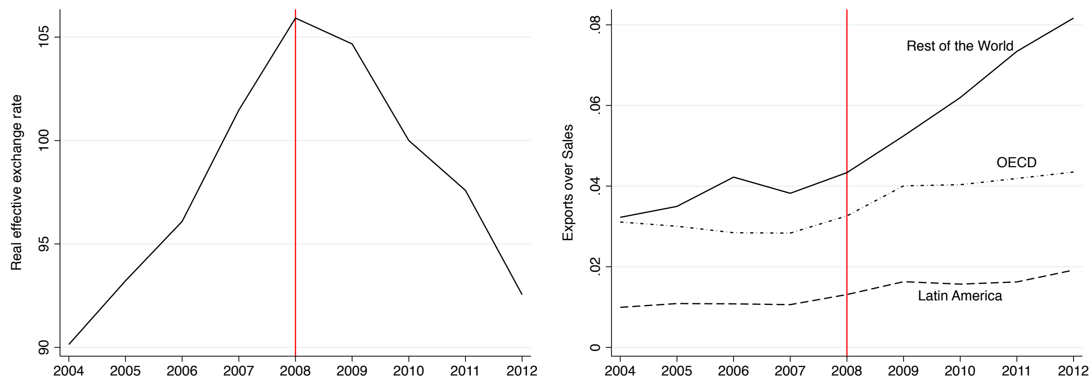
does not incorporate exports to Latin America because they remained relatively stable during the Great Recession. The ESEE dataset is suitable for the research question investigated in this paper even though the ideal dataset would report the value-added and input used for each product produced and exported separately for corresponding destinations.

The ESEE dataset includes other variables such as wage, input price index and debt to equity ratio. These variables play a crucial role in the analysis as they allow for controlling the cost shocks and financial health of firms. The panel also gives information on whether firms exited the market or were acquired by foreign investors in a given year. As I will discuss in the following sections, conditioning on survival and foreign ownership may generate bias in the estimations. Hence, I exclude the foreign owned firms and those exited the market between 2008 and 2012 from the main analyses.

Spain introduced the Employment Protection Legislation in 2012 that extended trial period of hiring additional workers for smaller firms with less than 50 employees. Garcia-Vega et al. (2021) find that this labor market reform increased innovative activities of firms by raising the flexibility in employment decisions. I take into account the possibility that labor market reform in 2012 might have had heterogeneous effects on firms with different characteristics. Therefore, I focus on the 2008-2012 period in order to abstract from productivity improving and innovative activities of exporters in response to the labor market reform.

Figure 3.1 provides graphical view of the underlying mechanism for the identification strategy. The change in the REER based on the unit labor costs is shown on the left panel. The REER has jumped to above 105 level in 2008 from 90 level in 2004 and declined thereafter to around 93 level by 2012. Many of the OECD countries and Spain are using the same currency (Euro) and experienced severe depression during the crisis. Thus, depreciation must have raised particularly the exports to low-income countries in destination portfolio while not affecting the OECD countries significantly. On the other hand, the movements in exports to sales ratio for each destination are displayed on the right panel. During the devaluation period, the share of exports in sales has increased sharply for the Rest of the World while remaining stable for the OECD countries and Latin America. The visual presentations suggest that firms' export intensity to low-income markets and exchange rate movements are evidently associated though it does not necessarily induce a causal relationship.

Figure 3.1: Real Effective Exchange Rate and Exports by Destination



Note: The left panel uses the IMF data on the real effective exchange rate based on unit labor costs normalized to 100 in 2010. The right panel uses the ESEE data and shows destination specific export intensities defined as the share of exports to a destination (the Rest of the World, OECD countries and Latin America) in total sales.

Table 3.1: Summary Statistics, Firm Characteristics, 2007

	Low-income exporter			High-income exporter		
	Mean	SD	Obs.	Mean	SD	Obs.
Export/Sales	0.368	0.278	704	0.414	0.277	578
Labor productivity (log)	11.628	0.635	704	11.659	0.658	578
Sales (log)	17.979	1.735	704	18.112	1.696	578
Capital investments (log)	13.068	4.264	704	13.193	4.371	578
R&D expenditure (log)	8.322	6.851	702	8.766	6.828	577
Patents	0.962	6.029	704	1.510	11.665	578

Notes: Table reports mean values, standard deviations and the number of observations of firm characteristics for the year 2007. Firms are grouped according to their status of exporting to low-income and high-income destinations. Firms exiting the market during the Great Recession and those acquired by foreign investors before and during the Great Recession are excluded.

Table 3.1 reports summary statistics for firms exporting to low-income destinations and high-income destinations in the pre-crisis year of 2007. It appears that high-income exporters initially depict better performance measures than low-income exporters: they have higher export share in sales, labor productivity, sales,

Table 3.2: Exports to Low-income Destinations in Sales across Industries 2008-2012

Industries	2008	2009	2010	2011	2012
1.Meat products	0.006	0.007	0.010	0.011	0.019
2.Food and tobacco	0.013	0.016	0.013	0.017	0.019
3.Beverage	0.016	0.018	0.040	0.042	0.042
4.Textiles and clothing	0.020	0.020	0.022	0.028	0.037
5.Leather, fur and footwear	0.022	0.025	0.027	0.031	0.031
6.Timber	0.002	0.003	0.009	0.011	0.009
7.Paper	0.025	0.022	0.029	0.034	0.025
8.Printing	0.004	0.002	0.005	0.004	0.008
9.Chemicals and pharmaceuticals	0.075	0.071	0.072	0.072	0.094
10.Plastic and rubber products	0.026	0.031	0.027	0.027	0.037
11.Nonmetal mineral products	0.028	0.025	0.041	0.049	0.065
12.Basic metal products	0.046	0.041	0.052	0.059	0.073
13.Fabricated metal products	0.020	0.020	0.025	0.029	0.034
14.Machinery and equipment	0.094	0.095	0.160	0.166	0.178
15.Computer products, electronics and optical	0.079	0.086	0.118	0.137	0.175
16.Electric materials and accessories	0.053	0.052	0.061	0.071	0.097
17.Vehicles and accessories	0.030	0.033	0.027	0.026	0.031
18.Other transport equipment	0.061	0.071	0.067	0.070	0.093
19.Furniture	0.023	0.029	0.035	0.038	0.048
20.Other manufacturing	0.038	0.030	0.034	0.039	0.044

Notes: Table reports the average level of exports to low-income destinations in sales across firms for each industry from 2008 to 2012. Low-income destinations are classified as countries except the OECD and the Latin American countries.

capital investments, R&D expenses and patents. Additionally, Table 3.2 reports the low-income exports over sales across industries from 2008 to 2012. In almost each industry, there has been an increase in low-income export intensity during the Great Recession.[8] In particularly some industries (e.g. Meat products, Beverage, Textiles and clothing, Timber, Printing, Nonmetal mineral products, Machinery and equipment, Computer products, electronics and optical, Furniture), the share of exports to low-income countries over sales more than doubled by the end of the period.

[8]Table B1 in the Appendix 3.A.1 shows the low-income export volumes across industries for the period 2008-2012.

3.3 Empirical Strategy

This section presents the empirical strategy. I introduce the empirical model and discuss the issues concerning the identification.

I start the analysis by investigating whether export status in 2007 can explain differential responses of the exports share to low-income and high-income destinations over sales to REER movements. Thus, I estimate the following equation:

$$\ln (E_{it}^{d}) = \alpha + \beta \ln (REER_t) * \mathbb{1}\{exports_{i2007} > 0\} + \gamma_i + \varepsilon_{it}, \qquad (3.1)$$

where E_{it}^{d} is the exports to destination d over sales and γ_i is the firm fixed effects. $\mathbb{1}\{exports_{i2007} > 0\}$ denotes the dummy for exporter status in 2007 that takes the value 1 if the firm was an exporter at that time and 0 otherwise. $REER_t$ is the real effective exchange rate, α is the constant and ε_{it} is the error term.

I am particularly interested in how destination of exports affected productivity improving activities and productivity gains of manufacturing firms in Spain. The 2008 global financial crisis provides a quasi-natural experiment with a sharp decline in REER in Spain during the Great Recession. As shown visually in the previous section, the REER devaluation must have increased the exports to low-income countries as products of Spanish exporters have become cheaper for consumers in low-income markets. Firms must have exported lower quality products to low-income markets due to lower willingness to pay of consumers for high quality, creating less incentive for upgrading despite an increased share of exports to low-income destinations in sales.

The main empirical concern in studying the effect of exporting on upgrading is the endogeneity of exporting. I overcome the endogeneity concern in this paper by exploiting the variations in REER during the Great Recession interacted with the firms' initial exports in sales, i.e. export intensity.[9] As shown on the left panel of Figure 3.1, the REER dropped sharply after 2008 despite a consistent increase in the pre-crisis period. I consider that Spanish firms must have gained international competitiveness against other countries due to lower growth of real wages to productivity, i.e. devaluation in the REER. In fact, within-firm

[9]Previously Park et al. (2010), Brambilla et al. (2012) and Bastos et al. (2018) used similar firm-level instruments based on various exchange rate measures. Gopinath and Neiman (2014) also highlights the role of firm behaviour in responses to exchange rate shocks that lead to the changes in aggregate productivity.

technological enhancements or resource allocation may also explain improved international competitiveness of firms but Eppinger et al. (2018) find that most of the manufacturing industries in Spain experienced a decline in TFP during the Great Recession, suggesting that they are unlikely the reasons of increased international competitiveness of firms.[10]

The instrument I need for the analysis must be correlated with the composition of exports across destinations. The exclusion restriction assumption requires that the instrument is exogenous to other determinants of productivity, innovation and upgrading activities of firms. To identify the causal effect of export intensity across destinations on firm productivity and upgrading, the instrument should predict the changes in export intensity across destinations and should not be correlated with firm productivity and cost shocks that may affect firm performance and upgrading efforts.

During the Great Recession, the changes in REER generated exogenous variations in exports to low-income countries because majority of the OECD countries use Euro as a national currency, i.e. relative competitiveness should not have altered much, and the effects of the crisis largely transmitted across developed economies. Given the large amount of tradable goods that are excluded from the consumption basket, I use the REER based on unit labor costs rather than based on consumer prices in construction of the instrument. To identify a source of variation in exports at the firm level, I use pre-determined export intensity, i.e. exports in sales, to exploit that firms those with initial attachments to export markets will differ in terms of their response to the changes in REER. Previously more intensely exporting firms should have adjusted by moving away from high-income markets (including domestic market, see Almunia et al. (2021)) and exported more to low-income destinations as they experience an increased competitiveness. Since consumers in low-income destinations have lower willingness to pay for higher quality, firms must have increased exports to low-income destinations because of devaluation against the currencies of low-income countries.

The instrument I use for the instrumental variable approach is defined as

$$z_{it} = \ln\Big(\frac{E_{i2007}}{R_{i2007}} \times REER_t\Big). \tag{3.2}$$

[10]Their findings correspond to the results presented in this paper such that firms experienced a reduction in productivity and efficiency measures though they increased their exports.

where the first term in the parenthesis is export intensity in which E_{i2007} and R_{i2007} denote firm's export and sales in 2007, respectively. Figure B7 in Appendix 3.A.2 plots the distribution of exports over sales in 2007 for firms exporting to low-income and high-income destinations. Distributions for both group display similar patterns whereas low-income exporters are initially less export intensive than high-income exporters.

I use Equation (3.2) to instrument for export intensity in each destination denoted as E_{it}^{d} and estimate the following equation:

$$\ln(\varphi_{it}) = \alpha \ln(E_{it}^{d}) + \beta X_{it} + \gamma_i + \varepsilon_{it} \tag{3.3}$$

where φ_{it} denotes the outcome variable of firm upgrading measures. X_{it} denotes control variables, γ_i denotes firm fixed effects and ε_{it} is the error term.

The crisis might have changed the workforce composition and affected cost structure of the firm. Exchange rate depreciations followed by large crises typically lead to substantial reductions in imports at the intensive margin (e.g. Gopinath and Neiman, 2014). Devaluation during the Great Recession might have made the access to imports more expensive or disruptions in labor market might have affected the wages, generating a differential cost shock for Spanish firms. To address these concerns, I control for average wage and input price at the firm level.[11]

Exporters may be financially healthier than non-exporters (e.g. Greenaway et al., 2007) though tighter credit constraints may disrupt international trade more than domestic sales because exporting is finance intensive compared to domestic sales (e.g. Amiti and Weinstein, 2011; Feenstra et al., 2014).[12] During the Great Recession, the role of financial constraints in export fall was limited in France (Bricongne et al., 2012) and in Belgium (Behrens et al., 2013) but imports in the US were severely affected by credit constraints (Chor and Manova, 2012). Hence, I control for debt capital in total equity to overcome the liquidity concerns of firms. I additionally control for industry fixed effects since financially more vulnerable

[11]Both devaluation in REER and reduced domestic demand might have restricted the access to Spanish market which limits the potential threat to identification that may arise from import competition.

[12]Exporters tend to be more exposed to financial constraints than firms selling only in domestic market because of higher input use, longer transaction and shipment times as they generate higher default risk and require external financing.

industries might have reduced their exports more (Bricongne et al., 2012; Chor and Manova, 2012).

Another concern for the identification is foreign ownership of firms. Foreign owned firms tend to perform better than domestic firms during the financial crises (Alfaro and Chen, 2012; Manova et al., 2015) and they are less affected because they have easier access to foreign capital markets (Amiti and Weinstein, 2011). Moreover, it might be cheaper to acquire a firm during the crisis because of devaluation or increased exports of firms might have attracted foreign investors. Foreign acquired firms might also more easily transfer technology and become more productive. For these reasons, I exclude foreign owned firms and whose share of foreign ownership increased above 50% during the Great Recession from the sample.

Finally, conditioning on firm survival may be important in identifying the true effect of exporting on productivity as well (Bernard and Jensen, 1999). I might underestimate the coefficient on exporting if I do not condition on firm survival because including exiting firms with low productivity would lead to downward bias in the estimations. To overcome this concern, I restrict the sample to firms surviving during this period in the estimations.

3.4 Results

This section presents the results. I estimate the model using labor productivity, innovation and various upgrading measures. Finally, I test the robustness of the underlying mechanism.

Table 3.3 reports the regression results from estimating Equation (3.1). The parameter of interest β is negative in all specifications. Since the REER was declining from 2008 to 2012, the results indicate that lower REER (devaluation) is associated with higher exports to each destination. Notice that exporters in 2007 increased their share of exports to low-income destinations in sales more than non-exporters in 2007 as shown in columns (1) and (2) while the effect on exporters and non-exporters are significant at the 1% and 10% levels, respectively. On the other hand, columns (3) and (4) show that devaluation in REER is also associated with larger exports to high-income destinations over sales. Similar to firms exporting to low-income destinations, exporters in 2007 experienced larger increases in the share of exports to high-income destinations in sales over time

Table 3.3: Real Effective Exchange Rate Movements and Initial Exporting Status

	Low-income Exports/Sales		High-income Exports/Sales	
	(1)	(2)	(3)	(4)
log(REER) × Exporting status in 2007 (=0)	-0.112***	-0.0414*	-0.0236	-0.00971*
	(0.0232)	(0.0232)	(0.0203)	(0.00510)
log(REER) × Exporting status in 2007 (=1)	-0.100***	-0.145***	-0.0148	-0.0446
	(0.0230)	(0.0319)	(0.0202)	(0.0310)
Observations	5662	5593	5662	5593
Firm fixed effects	No	Yes	No	Yes
Industry fixed effects	No	Yes	No	Yes
Region fixed effects	No	Yes	No	Yes
R^2	0.079	0.832	0.063	0.799

Notes: Table reports how real effective exchange rate movements affected exports to low-income and high-income destinations in sales conditional on the exporting status in 2007. Firms exiting the market during the Great Recession and those acquired by foreign investors before and during the Great Recession are excluded from the estimations. Standard errors are clustered at the firm level. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

but the coefficient estimate for exporters in 2007 is insignificant.

The results suggest that previously exporting firms responded to REER devaluation by increasing the share of exports to low-income destinations in sales more than firms only attached to local market in 2007. In contrast, for firms attached to export markets before the Great Recession, devaluation in the REER did not affect the share of exports to high-income destinations in sales.

This finding indicates that exporter status in the pre-crisis period is an important determinant in explaining the impact of REER devaluation on exports across different destinations, justifying the validity of the components of the instrument. However, exports over sales provides a broader measure than export status because it captures both intensive and extensive margins of trade activity. Therefore, to construct the instrument in the following part of the analysis, I interact the exports over sales rather than using a dummy for exporting status with the REER.

3.4.1 Export Destinations and Labor Productivity

I proceed the analysis by estimating Equation (3.3) with labor productivity as the outcome variable. Table 3.4 reports the results of IV regressions for each destination. Columns (1)-(3) present the estimation results for how exports to low-income destinations impacted labor productivity. All specifications include firm, industry and region fixed effects. Column (1) presents the results with only fixed effects. The parameter of interest is negative and statistically significant at the 1% level. Column (2) shows that the impact on labor productivity is slightly smaller in magnitude when controlled for input materials price and wage. Notably, wage is positively and significantly associated with labor productivity. Column (3) reports the coefficient estimated as debt to equity ratio is additionally controlled for. Conditional on cost shocks and financial health of the firm, the estimation results for the exports to low-income destinations in sales are robustly negative and always statistically significantly different from zero at 1% level. The instrument predicts the endogenous regressor at the first stage and Kleibergen-Paap F-statistic is sufficiently large around 16 in all specifications.

Columns (4)-(6) present the results for how exports to high-income destinations in sales affected labor productivity. Column (1) reports baseline regression results without controls, Column (2) includes input material price and wage to control for cost shocks and Column (3) includes debt to equity ratio to control

Table 3.4: Export Destinations and Labor Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
Low-income Exports/Sales	-0.0820***	-0.0691***	-0.0694***			
	(0.0231)	(0.0201)	(0.0201)			
High-income Exports/Sales				-0.384	-0.317	-0.326
				(0.395)	(0.318)	(0.333)
Input price change (%)		-0.0207	-0.0205		-0.0855	-0.0865
		(0.124)	(0.124)		(0.314)	(0.323)
Log wage		0.850***	0.850***		0.923***	0.924***
		(0.0583)	(0.0584)		(0.167)	(0.172)
Debt/Equity			0.0183*			0.106
			(0.0101)			(0.0897)
Observations	5226	5226	5226	5226	5226	5226
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-statistic	16.07	16.07	16.20	0.95	1.00	0.96

Notes: Dependent variable is log labor productivity, i.e. value-added per worker. Columns (1)-(3) report the coefficients for exports to low-income destinations in sales and Columns (4)-(6) report the coefficients for exports to high-income destinations in sales. Columns (3) and (6) include the full set of controls. Firms exiting the market during the Great Recession and those acquired by foreign investors before and during the Great Recession are excluded from the estimations. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

for financial health of firms. On the contrary to the findings for the exports to low-income destinationss, the coefficient estimate on exports to high-income destinations in sales is never statistically significant, suggesting that the changes in the intensity of exports to high-income destinations did not affect labor productivity. Moreover, Kleibergen-Paap F-statistic for the first-stage estimation is very weak in each specification. Overall, I find that one unit increase of exports to low-income destinations in sales reduces labor productivity by around 6.9% but higher share of exports to high-income destinations does not. The results indicate that the movements in REER raised the share of exports to low-income destinations in sales that led to lower labor productivity while did not affect the share of exports to high-income destinations in sales and they remained robust to various identification threats.

Table B2 in the Appendix 3.A.1 partially tests the validity of exclusion restriction assumption by regressing the control variables on the instrument. Wage is positively and input price is negatively correlated with the instrument, significant at the 1% level. Although the control variables are significantly associated with the instrument, the findings are robust to inclusion of controls, suggesting that control variables do not violate exclusion restriction assumption.

Recall that labor productivity is defined as value-added per worker. Hence, the negative coefficients presented in Table 3.4 might be because employment increased more than value-added, employment increased while value-added decreased or employment decreased less than value-added. I present the results of estimating value-added and employment separately in Table B3. The coefficient estimates for both value-added and employment are negative and statistically significantly different from zero at the 1% level. However, notice that the fall in value-added (-0.135 in the specification with full controls) is larger than the fall in employment (-0.065 in the specification with full controls), inducing a decrease in labor productivity.

Table B4 reports the additional results by including exiting firms between 2008 and 2012. As explained in Section 3.3, the coefficients for these regressions in Columns (1), (2) and (3) are smaller in magnitude than Table 3.4 because of downward bias arising from including exiting low productivity firms. The coefficient estimates are robust to the inclusion of full set of controls. Again, first-stage Kleibergen-Paap F-statistic is sufficiently large for low-income exporters but very weak for high-income exporters. Additionally, Table B5 presents the results when foreign owned firms are included in the estimations. In this case, the estimations are slightly upward biased because foreign owned firms tend to be more resilient to financial crises and have higher productivity (Amiti and Weinstein, 2011; Alfaro and Chen, 2012; Manova et al., 2015). Table B6 in Appendix 3.A.1 provides reduced form estimation results with labor productivity is the dependent variable and the instrument is independent variable.

3.4.2 Export Destinations and Innovation Activities of Firms

I reestimate the model by using various innovation activity measures. Table 3.5 reports the results from regressing innovation measures on the shares of exports to low-income and high-income destinations in sales while controlling for cost shocks (wage and input price), financial health (debt to equity ratio) and firm, industry, region fixed effects. Panel A presents the results for the exports to low-income destinations. The estimated coefficient on log R&D expenditure is equal to -0.323 (significant at the five percent level) and the estimated coefficient on log patents is equal to -0.0338 (significant at the one percent level). Column (1)

Table 3.5: Export Destinations and Innovation Activities

	(1) R&D	(2) Patents	(3) Product Innovation	(4) Process Innovation
Panel A:				
Low-income destination				
Low-income Exports/Sales	-0.323**	-0.0338***	-0.0142	-0.0255*
	(0.133)	(0.0128)	(0.00977)	(0.0136)
Input price change (%)	0.0720	-0.0122	-0.0843	0.0347
	(0.671)	(0.0604)	(0.0589)	(0.0929)
Log wage	-0.123	-0.0146	-0.0292	0.0220
	(0.259)	(0.0321)	(0.0247)	(0.0365)
Debt/Equity	-0.0683	-0.0152***	-0.00104	-0.000401
	(0.0478)	(0.00538)	(0.00400)	(0.00725)
Observations	5220	5220	5220	5220
Firm fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
First-stage F-statistic	16.95	16.95	16.95	16.95
Panel B:				
High-income destination				
High-income Exports/Sales	-1.603	-0.167	-0.0702	-0.126
	(1.769)	(0.183)	(0.0872)	(0.146)
Input price change (%)	-0.234	-0.0441	-0.0977	0.0106
	(1.598)	(0.168)	(0.0841)	(0.147)
Log wage	0.237	0.0231	-0.0134	0.0504
	(0.858)	(0.0899)	(0.0430)	(0.0731)
Debt/Equity	0.360	0.0296	0.0177	0.0334
	(0.448)	(0.0493)	(0.0218)	(0.0363)
Observations	5220	5220	5220	5220
Firm fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
First-stage F-statistic	0.89	0.89	0.89	0.89

Notes: Table reports the effects of exports to low-income and high-income destinations on innovative activities. Panel A and B show the results for low-income and high-income export destinations, respectively. Dependent variables are log R&D expenses in Column (1), inverse hyperbolic sine of patents in Column (2), dummy product innovation in Column (3) and dummy process innovation in Column (4). All regressions include the full set of controls. Firms exiting the market during the Great Recession and those acquired by foreign investors before and during the Great Recession are excluded from the estimations. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

and (2) report that one unit increase in the share of low-income exports in sales reduces R&D expenditures by 32 percentage points and patents 3.3 percentage points, respectively. Specifications in Column (3) and (4) present the results for binary product and process innovation indicators. Both of the coefficient estimates are negative while only process innovation is statistically significant at the 10% level. Furthermore, first-stage F-statistics are sufficiently above the conventional threshold of 10.

Results for the exports to high-income destinations are shown in Panel B. The estimated coefficients are statistically insignificant in all specifications. As in previous estimations, the instrument is not able to predict the changes in the share of exports to high-income destinations in sales at the first stage. These findings suggest that firms which raised share of exports to low-income destinations in total sales during the crisis period reduced their innovative activities in addition to labor productivity. However, the share of exports to high-income destinations in sales has remained unchanged and did not affect the innovation activities of firms.

3.4.3 Efforts for Upgrading

The regression results show that firms experienced a fall in various productivity measures. One reason of this might be that firms intentionally reduced their efforts for upgrading in order to adjust the quality of their product portfolio to low-income destinations where the willingness to pay for high-quality product is low. An alternative explanation for this pattern is that they might have received a specific shock that led to lower productivity. I investigate how exports to low-income and high-income destinations affected various direct measures of upgrading efforts to test which mechanism is inducing a reduction in productivity.

Table 3.6 reports the results. All specifications have dummy dependent variables and include the full set of controls. Column (1) reports the coefficient estimate on technological cooperation agreements. Column (2), (3), (4) and (5) present the estimates for technological collaboration with customers, competitors, suppliers and universities and/or technological parks, respectively. Column (6) shows the estimated coefficient for whether firms used advisors and/or experts for obtaining information about technology.

Panel A presents the estimates for the exports to low-income destinations with all coefficients are negative but only technological cooperations with customers in

Table 3.6: Upgrading Efforts with Technological Cooperations

	(1) Agreements	(2) Customers	(3) Competitors	(4) Suppliers	(5) Universities	(6) Advisors
Panel A						
Low-income	0.0000191	-0.0132*	-0.00211	0.00855	-0.0163*	-0.0124
	(0.00464)	(0.00792)	(0.00452)	(0.00952)	(0.00979)	(0.00979)
Input price	0.0536*	0.0456	0.0227	0.0856	0.0192	0.0164
	(0.0274)	(0.0529)	(0.0301)	(0.0676)	(0.0593)	(0.0607)
Log wage	-0.0119	-0.0208	-0.00723	-0.00231	-0.00931	-0.00185
	(0.00780)	(0.0172)	(0.00582)	(0.0210)	(0.0211)	(0.0230)
Debt/Equity	0.000565	-0.00349	-0.000384	-0.000306	-0.0242***	0.00940
	(0.00149)	(0.00224)	(0.00158)	(0.00349)	(0.00773)	(0.0134)
Observations	5226	5226	5226	5226	5226	5226
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-statistic	16.20	16.20	16.20	16.20	16.20	16.20
Panel B						
High-income	0.0000894	-0.0621	-0.00990	0.0401	-0.0764	-0.0580
	(0.0218)	(0.0731)	(0.0227)	(0.0588)	(0.0888)	(0.0720)
Input price	0.0537*	0.0330	0.0207	0.0937	0.00376	0.00469
	(0.0283)	(0.0817)	(0.0335)	(0.0742)	(0.0936)	(0.0798)
Log wage	-0.0120	-0.00677	-0.00499	-0.0114	0.00799	0.0113
	(0.00857)	(0.0367)	(0.00905)	(0.0295)	(0.0485)	(0.0364)
Debt/Equity	0.000541	0.0133	0.00229	-0.0111	-0.00365	0.0250
	(0.00494)	(0.0184)	(0.00531)	(0.0141)	(0.0215)	(0.0255)
Observations	5226	5226	5226	5226	5226	5226
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-statistic	0.96	0.96	0.96	0.96	0.96	0.96

Notes: Table reports the effects of exports to low-income and high-income destinations on upgrading efforts of firms. Panel A and B show the results for low-income and high-income export destinations, respectively. Low-income and High-income respectively represent the exports in sales destined to low-income destinations. Input price represents the input price change in percentage. All dependent variables are dummy variables; technological cooperation agreements in Column (1), technological collaboration with customers in Column (2), technological collaboration with competitors in Column (3), technological collaboration with suppliers in Column (4), technological collaboration with universities and/or technological parks in Column (5) and using advisors and/or experts for getting information about technology in Column (6). All regressions include the full set of controls. Firms exiting the market during the Great Recession and those acquired by foreign investors before and during the Great Recession are excluded from the estimations. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Column (2) and with universities or technological parks in Column (5) are statistically significant at the 10% level. The first-stage estimates in each specification suggest that Kleibergen-Paap F-statistics are sufficiently strong. In Panel B, I report the results for the exports to high-income destinations. As expected, my instrument does not predict the regressor of the share of exports to high-income destinations in sales at the first-stage and the coefficient estimates are never significant in any specification. These results indicate that firms did not attempt to upgrade their technology by collaborating different agents or receiving consultancy service on technology use. Hence, it is not surprising that firms experienced a decline in productivity given the evidence that they reduced their efforts for upgrading.

3.4.4 Quality Downgrading

Several recent studies find that firms adjust the quality of their products in response to the changes in exchange rate movements. For instance, Fauceglia (2020) and Freitag and Lein (2023) document that Swiss appreciation induced an increase in quality of exported goods. Similarly in Spain, firms might have adjusted to REER devaluation by producing lower quality products to increase exports to low-income destinations and this quality downgrading mechanism might explain lowered productivity durign the Great Recession. Finding direct measure of product quality is often difficult and the literature generally used the output price as a proxy. I only observe the sales price changes of firms in the dataset that might reflect the product quality and regress the log output price index on the share of exports to low-income and high-income destinations in sales to test quality downgrading mechanism.

Table 3.7 present the results. Column (1) includes only fixed effects and the coefficient on exports to low-income destinations is 0.0126 statistically significant at the 1% level. In Column (2), I lose the significance on the coefficient estimate and the magnitude drops sharply while controlling for input materials price and wage. The coefficient on input material price is 0.186 and statistically significant at the 1% level. Thus, these findings suggest a pass-through effect of input price on output price. As shown in Column (3), the coefficient on the share of exports to low-income destinations in sales remains largely the same in magnitude and statistically not different from zero when debt to equity ratio is additionally controlled for. In all specifications, first-stage estimates are sufficiently strong.

Table 3.7: Export Destinations and Quality Downgrading

	(1)	(2)	(3)	(4)	(5)	(6)
Low-income Exports/Sales	0.0126***	0.000755	0.000763			
	(0.00385)	(0.00276)	(0.00275)			
High-income Exports/Sales				0.0627	0.00590	0.00618
				(0.0720)	(0.0250)	(0.0261)
Log input price		0.186***	0.186***		0.178***	0.178***
		(0.0315)	(0.0315)		(0.0541)	(0.0551)
Log wage		-0.00362	-0.00362		-0.00534	-0.00539
		(0.00733)	(0.00733)		(0.0102)	(0.0104)
Debt/Equity			-0.000467			-0.00204
			(0.000815)			(0.00612)
Observations	5394	5394	5394	5394	5394	5394
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-statistic	18.05	15.76	15.87	0.79	0.32	0.30

Notes: Table reports the response of output prices to the changes in exports to low-income and high-income destinations in sales. Dependent variable is firm-level log output price index. Columns (1)-(3) report the coefficients for low-income exports in sales and Columns (4)-(6) report the coefficients for high-income exports in sales. Columns (3) and (6) include the full set of controls. Firms exiting the market during the Great Recession and those acquired by foreign investors before and during the Great Recession are excluded from the estimations. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Columns (4) reports the estimated coefficient with only fixed effects that is positive but statistically insignificant. Column (5) and (6) present the results while controlling for cost shocks and financial health. The coefficient on the share of exports to high-income destinations in sales remains insignificant. In all specifications, the instrument fails to predict changes in exports to high-income destinations with weak first-stage F-statistics. Using the output price as quality, I find that firms passed the input materials price changes through their output prices.

3.5 Conclusion

This paper investigated the effects of exports to low-income and high-income destinations on firm productivity and upgrading efforts in Spanish manufacturing industries from 2008 to 2012. I exploited the changes in REER during the Great Recession for the identification of heterogeneous effects on firms exporting to low-income and high-income destinations. I find that devaluation raised the share of exports to low-income destinations which induced a decline in productivity and upgrading efforts. In contrast, the share of exports to high-income destinations did not change in response to REER devaluation as well as productivity and upgrading efforts.

The findings in this paper suggest that market destination can determine the gains from exporting rather than exporting per se. However, external validity of the results are worth to investigate in the future work. An advantage of this paper is that I use the data on both direct upgrading activities and firms' attempts for upgrading in the analysis, which allows me to abstract from the shortcomings of TFP measures (Verhoogen, 2021). The results support quality sorting hypothesis that links product quality to firm productivity.

The important question unanswered is whether increased share of exports to low-income destinations induced a decline in productivity and upgrading efforts because of lower competition in low-income markets, lower willingness to pay of low-income consumers for high quality products or different technology and skills required for producing low quality products. The dataset used in the analysis does not provide information on the market structure and consumer preferences in export destinations. Hence, I regard exploring these channels as interesting avenues for future research.

This paper highlights that considering market destination in studies examining the effects of exporting on efficiency improvements and upgrading efforts may be particularly important for policymakers. Advocating the contents of globalization may require evaluating the gains from trade from a broader perspective and additional policy tools to promote firm-level upgrading might be needed to maximize trade related efficiency gains.

3.A Appendices to Chapter 3

3.A.1 Appendix Tables

Table B1: Total Low-income Exports across Industries 2008-2012

Industries	2008	2009	2010	2011	2012
1.Meat products	17.297	17.415	17.978	18.153	18.503
2.Food and tobacco	19.842	19.971	19.552	19.899	19.871
3.Beverage	18.057	17.696	17.999	18.019	18.079
4.Textiles and clothing	17.529	17.394	17.737	17.767	17.747
5.Leather, fur and footwear	15.343	15.567	16.344	16.463	16.887
6.Timber	16.532	16.206	16.621	16.925	16.017
7.Paper	19.209	19.166	19.719	19.737	19.625
8.Printing	16.756	16.106	16.549	16.438	16.218
9.Chemicals and pharmaceuticals	21.081	20.959	20.807	20.897	20.978
10.Plastic and rubber products	19.828	19.655	18.569	18.638	18.831
11.Nonmetal mineral products	19.495	19.390	19.574	19.728	19.817
12.Basic metal products	20.455	20.008	20.896	20.852	20.750
13.Fabricated metal products	19.586	19.354	19.351	19.522	19.579
14.Machinery and equipment	19.682	19.316	19.762	19.757	19.871
15.Computer products, electronics and optical	19.224	19.065	18.870	19.145	19.383
16.Electric materials and accessories	19.872	19.620	20.054	20.179	20.237
17.Vehicles and accessories	20.760	20.693	21.197	21.650	21.650
18.Other transport equipment	20.291	20.957	20.990	20.784	20.813
19.Furniture	16.706	16.963	17.652	17.910	17.946
20.Other manufacturing	17.312	16.214	16.080	16.075	16.154

Notes: Table reports total annual low-income exports in the sample across industries from 2008 to 2012. Low-income destinations are classified as countries except the OECD and the Latin American countries.

Table B2: Relationship between the Instrument and the Control Variables

	Log Wage		Input price(%)		Debt/Equity	
	(1)	(2)	(3)	(4)	(5)	(6)
Instrument	0.224***	0.224***	-0.0918***	-0.0918***	-0.286	-0.286
	(0.0604)	(0.0606)	(0.0279)	(0.0280)	(0.258)	(0.259)
Observations	5256	5256	5256	5256	5256	5256
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	No	Yes	No	Yes
Region fixed effects	No	Yes	No	Yes	No	Yes
R^2	0.87	0.87	0.30	0.30	0.25	0.25

Notes: Table reports the correlations between the instrument and the control variables used in the analysis. Dependent variables are log wage in Columns (1)-(2), percentage change in input price in Columns (3)-(4) and debt to equity ratio in Columns (5) and (6). Firms exiting the market during the Great Recession are excluded but those acquired by foreign investors are included. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table B3: Export Destinations, Value-Added and Employment

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Value-Added						
Low-income Exports/Sales	-0.139***	-0.135***	-0.135***			
	(0.0367)	(0.0359)	(0.0357)			
High-income Exports/Sales				-0.650	-0.618	-0.633
				(0.668)	(0.619)	(0.645)
Input price change (%)		-0.00587	-0.00591		-0.133	-0.134
		(0.182)	(0.181)		(0.596)	(0.609)
Log wage		0.257***	0.257***		0.399	0.400
		(0.0885)	(0.0885)		(0.319)	(0.327)
Debt/Equity			-0.00507			0.166
			(0.0123)			(0.169)
Observations	5226	5226	5226	5226	5226	5226
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-statistic	16.07	16.07	16.20	0.95	1.00	0.96
Panel B: Employment						
Low-income Exports/Sales	-0.0567***	-0.0655***	-0.0650***			
	(0.0158)	(0.0179)	(0.0177)			
High-income Exports/Sales				-0.265	-0.300	-0.305
				(0.274)	(0.302)	(0.313)
Input price change (%)		0.0139	0.0137		-0.0476	-0.0481
		(0.0826)	(0.0821)		(0.289)	(0.294)
Log wage		-0.581***	-0.580***		-0.512***	-0.511***
		(0.0591)	(0.0590)		(0.160)	(0.163)
Debt/Equity			-0.0234**			0.0589
			(0.0111)			(0.0797)
Observations	5226	5226	5226	5226	5226	5226
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-statistic	16.07	16.07	16.20	0.95	1.00	0.96

Notes: Table reports the effects of exports to low-income and high-income destinations on value-added and employment. Panel A presents the results for value-added and Panel B presents the results for employment. Columns (3) and (6) include the full set of controls. Firms exiting the market during the Great Recession and those acquired by foreign investors before and during the Great Recession are excluded from the estimations. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table B4: Export Destinations and Labor Productivity, Including Exiting Firms

	(1)	(2)	(3)	(4)	(5)	(6)
Low-income Exports/Sales	-0.0897***	-0.0765***	-0.0768***			
	(0.0255)	(0.0223)	(0.0223)			
High-income Exports/Sales				-0.427	-0.355	-0.365
				(0.455)	(0.368)	(0.386)
Input price change (%)		-0.00270	-0.00259		-0.0901	-0.0919
		(0.129)	(0.129)		(0.346)	(0.355)
Log wage		0.880***	0.880***		0.966***	0.968***
		(0.0615)	(0.0616)		(0.180)	(0.185)
Debt/Equity			0.0164			0.113
			(0.0101)			(0.101)
Observations	5504	5504	5504	5504	5504	5504
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	No	Yes	Yes
Region fixed effects	No	Yes	Yes	No	Yes	Yes
First-stage F-statistic	15.37	15.38	15.51	0.89	0.94	0.90

Notes: Dependent variable is log labor productivity, i.e. value-added per worker. Columns (1)-(3) report the coefficients for low-income exports in sales and Columns (4)-(6) report the coefficients for high-income exports in sales. Columns (3) and (6) include the full set of controls. Firms exiting the market during the Great Recession are included but those acquired by foreign investors are excluded. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table B5: Export Destinations and Labor Productivity, Including Foreign Acquired Firms

	(1)	(2)	(3)	(4)	(5)	(6)
Low-income Exports/Sales	-0.0743***	-0.0680***	-0.0682***			
	(0.0216)	(0.0200)	(0.0199)			
High-income Exports/Sales				-3.152	-2.966	-3.631
				(27.59)	(26.68)	(39.69)
Input price change (%)		0.0136	0.0138		0.651	0.806
		(0.125)	(0.125)		(6.203)	(9.115)
Log wage		0.851***	0.851***		1.100	1.144
		(0.0546)	(0.0546)		(2.507)	(3.492)
Debt/Equity			0.0160			0.899
			(0.0118)			(9.527)
Observations	6243	6243	6243	6243	6243	6243
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	No	Yes	Yes
Region fixed effects	No	Yes	Yes	No	Yes	Yes
First-stage F-statistic	15.96	15.99	16.12	0.01	0.01	0.01

Notes: Dependent variable is log labor productivity, i.e. value-added per worker. Columns (1)-(3) report the coefficients for low-income exports in sales and Columns (4)-(6) report the coefficients for high-income exports in sales. Columns (3) and (6) include full controls. Firms exiting the market during the Great Recession are excluded but those acquired by foreign investors are included. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

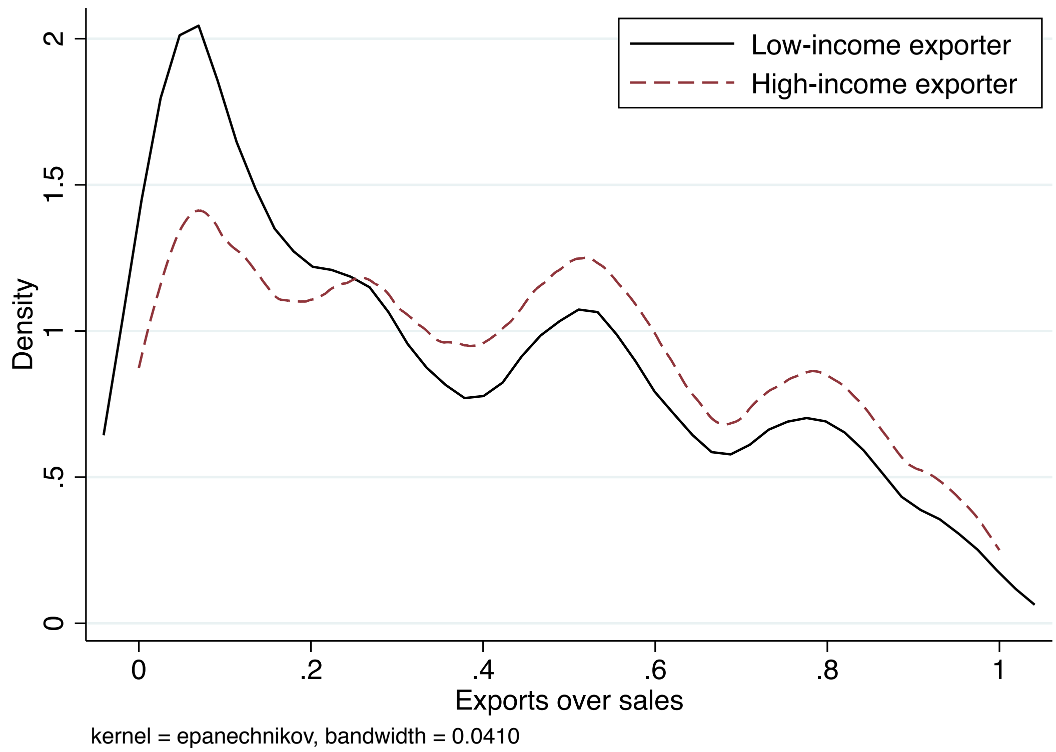
Table B6: Reduced Form Estimations

	(1)	(2)	(3)	(4)	(5)
Instrument	0.0856***	1.252***	1.252***	1.056***	1.066***
	(0.00790)	(0.170)	(0.170)	(0.166)	(0.162)
Input price change (%)			-0.00573	-0.0195	-0.0192
			(0.101)	(0.0986)	(0.0986)
Log wage				0.848***	0.847***
				(0.0518)	(0.0518)
Debt/Equity					0.0358**
					(0.0162)
Observations	5312	5226	5226	5226	5226
Firm fixed effects	No	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	Yes	Yes
Region fixed effects	No	Yes	Yes	Yes	Yes
R^2	0.07	0.71	0.71	0.74	0.74

Notes: Table reports the reduced form estimations. Dependent variable is log labor productivity. Firms exited the market during the Great Recession and those acquired by foreign investors before and during the Great Recession are excluded from the estimations. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

3.A.2 Appendix Figures

Figure B7: Distributions of Export Intensity in 2007



Note: Graph shows the distribution of export intensities (exports in sales) of low-income and high-income exporters in 2007.

3.A.3 List of variables

Upgrading efforts

TECHNOLOGICAL COOPERATION WITH CUSTOMERS (CTCL): Categorical variable which indicates whether the company maintained a technological collaboration with customers. Categories - No - Yes.

TECHNOLOGICAL COOPERATION WITH COMPETITORS (CTCO): Categorical variable which indicates whether the company maintained a technological collaboration with competitors Categories - No - Yes.

TECHNOLOGICAL COOPERATION WITH SUPPLIERS (CTPR): Categorical variable which indicates whether the company maintained a technological collaboration with suppliers. Categories - No - Yes.

TECHNOLOGICAL COOPERATION AGREEMENTS (ACT): Categorial variable which indicates whether the company had technological cooperation agreements (joint venture). Categories: - No - Yes.

COLLABORATION WITH UNIVERSITIES AND/OR TECHNOLOGICAL (CUCT): Categorial variable which indicates whether the company collaborated with universities and/or technological parks. Categories: - No - Yes.

USE OF ADVISORS FOR GETTING INFORMATION ABOUT TECHNOLOGY (UAIT): Categorial variable which indicates whether the company used advisors and/or experts for getting information about technology . Categories: - No - Yes.

Innovation activities

PATENTS REGISTERED IN SPAIN (PATESP): Number of patents filed in Spain by the company during the year.

PATENTS REGISTERED ABROAD (PATEXT): Number of patents filed abroad by the company during the year.

PATENTS: Sum of PATESP and PATEXT in a given year.

TOTAL EXPENSES IN R&D (GTID): Total expenses in R&D activities during the year, expressed in Euros.

PROCESS INNOVATIONS (IPR): Categorial variable which idicates whether the company has achieved process innovations during the financial year. Categories of the variable: - Yes - No.

PRODUCT INNOVATIONS (IP): Categorial variable which indicates whether the company has achieved product innovations during the financial year. Categories of the variable: - No - Yes.

Chapter 4

Labor Market Monopsony and Firm Behavior: Evidence from Spanish Exporters

4.1 Introduction

Firms' labor market power has been a growing concern in recent years because increasing number of empirical evidences reflect the presence of market failures. Although monopsony (or oligopsony) power has been largely neglected for a long time since the idea was originated with Robinson (1933), we have an accumulated evidence today and a growing consensus on rising monopsony power of firms in labor markets across various industries and countries (See Boal and Ransom, 1997; Ashenfelter et al., 2010; Manning, 2011; Sokolova and Sorensen, 2021; Manning, 2021; Ashenfelter et al., 2022; Card, 2022, for review studies on the topic). Rapidly growing empirical literature suggests that employers possess some market power in wage setting and such labor market irregularities unlikely comply with perfectly competitive models.

Monopsony power in labor market refers to a case in which there is a single buyer (an employer) and many sellers in the market (workers).[1] Theoretically,

[1]More typical market structures tend to be those with few employers and many workers and referred as oligopsony or monopolistic competition, see Bhaskar et al. (2002) for a detailed discussion. However, I prefer to use the term monopsony power in the remaining of the paper because the method I introduce is an extension of the standard monopsony model.

monopsonistic labor market induces that labor supply curve to a firm is not infinitely elastic and firms face upward sloping labor supply curve. In that case, wage is not equated to marginal revenue generated by workers and workers are paid less than their worth to the firm.[2]

Search frictions and idiosyncratic preferences of workers are considered to be the main sources of labor market frictions. Geographical restrictions and workers' lack of information about better or similar outside job opportunities generate search frictions because matching between employers and workers (searching, finding and changing a job) is a costly process and it takes time (Burdett and Mortensen, 1998; Manning, 2011). In the models of idiosyncratic preferences, workers have heterogeneous preferences in job search and idiosyncratic utility of different jobs allows firms to exploit workers (Card et al., 2018). More recently, a growing body of literature also emphasizes that firms may gain monopsony power because of employer concentration (e.g. Benmelech et al., 2022; Azar et al., 2022), tax changes (e.g. Berger et al., 2022), institutional settings and legal restrictions to mobility (e.g. Naidu, 2010; Naidu and Yuchtman, 2013; Naidu et al., 2016; Krueger and Ashenfelter, 2022; Balasubramanian et al., 2022).

Market failures and anti-competitive practices in product markets have been major concerns among academics, lawyers and antitrust authorities over the past decades but the implications of antitrust in labor markets have been neglected (Posner, 2021). However, strategic interactions of firms can be subject to antitrust enforcement because collusive and anti-competitive behavior might lead to concentration of employers and generate imperfections in labor markets. In this respect, recent studies discover that monopsonistic competition in labor market may arise because of no-poaching and non-solicidation agreements (e.g. Ashenfelter et al., 2022), non-compete clauses (e.g. Balasubramanian et al., 2022), franchise agreements (e.g. Krueger and Ashenfelter, 2022) and mergers and acquisitions (e.g. Arnold, 2019; Prager and Schmitt, 2021).[3]

[2]In contrast, perfectly competitive labor market induces that workers seek better job options and reduce their labor supply if the firm deviates from the wage determined at the market level. Wage elasticity of labor supply curve to the firm then becomes infinitely elastic and thus the employer loses its workers when it cuts wages. In other words, firms do not have wage-setting power if labor market is competitive ($\partial W/\partial L = 0$) and labor supply elasticity becomes equal to zero $\varepsilon = 0$. In this case, marginal revenue product of labor becomes equal to wage $MRPL/W = 1$ and workers are paid as much as they contribute to the firm revenue.

[3]See Naidu et al. (2018) and Naidu and Posner (2022) for the discussions on whether

How does exporting affects monopsony power of firms in labor markets? In this paper, I develop a simple empirical method to measure the impact of a firm's decision on its monopsony power in labor market. Using this model and exploiting China's accession to the World Trade Organization (WTO) in a difference-in-differences setting, I estimate the impact of increased exports on monopsony power of Spanish manufacturing firms. I find that more intensely exporting firms paid their workers around 39-49% of their marginal revenue product, which declined from 60-88% in absence of the effect of exports. Hence, higher exports reduced workers' pay by 36-45% for the period 2002-2007 compared to 1996-2001.

The findings additionally suggest that higher exports reduced labor share and labor productivity. More intensely exporting raised the demand for low-skill workers while did not affect the employment of high-skill workers within firms but induced higher temporary contracts in some industries during the 2002-2007 period. The results in this paper provide robust evidences on increased labor market power of exporting firms and suggest that additional public policies might be needed to address trade induced labor market monopsony.

The main contribution of this paper is to develop a new framework to estimate the effect of firm-level decisions on their monopsony power in labor markets. Labor economics literature developed several methods to measure monopsony power while many studies in recent years adopted a framework proposed by De Loecker and Warzynski (2012). Relying on production function estimation and the assumption of a perfectly competitive materials market, their approach is originally developed to measure markups but also allows to obtain firm-level labor supply elasticity (wage markdowns).[4] My approach is simple and neither requires estimating the production function nor relies on strong assumptions. Hence, the model introduced in this paper is not restrictive and it can be implemented using any choice variable of a firm.

Standard approach in labor economics literature estimates the labor supply elasticity that captures the gap between marginal revenue contribution of the worker and average wage (e.g. Falch, 2010; Staiger et al., 2010). On the other hand, Manning (2003) provides an alternative framework referred as dynamic monopsony. Based on the dynamic decision-making processes of workers and employers, his method incorporates the elasticities of recruitment and quit functions

anti-trust policies can correct imperfections in labor markets.

[4]See Doraszelski and Jaumandreu (2021) and Bond et al. (2021) for strong criticisms on the estimation procedure of De Loecker and Warzynski (2012).

(e.g. Hirsch et al., 2010; Ransom and Sims, 2010). A recently growing body of papers utilize the insights from the industrial organization (IO) literature and explain monopsony power with employer concentration based on Cournot oligopsony model. These studies measure concentration ratios of vacancies or employers such as Herfindahl-Hirschman Index (HHI) (e.g. Azar et al., 2020; Benmelech et al., 2022; Azar et al., 2022).[5] The methodology I introduce extends the textbook model of monopsony in a way that it allows to identify how much a firm activity increases or decreases firms' labor market power. Therefore, my approach differs from the current models that examine whether or how much firms have market power, which is a different research question.

I additionally contribute to recently growing empirical trade literature investigating the labor market outcomes of trade in presence of labor market imperfections. Previous trade models tended to rely on the assumption of perfectly competitive labor markets and the role of firms' labor market monopsony power has received little attention until recently. Focusing on China's accession to WTO in 2001, Lu et al. (2019) find that FDI liberalization increased monopsony power in China while Kondo et al. (2022) find that input trade liberalization reduced labor market monopsony power of Chinese firms. Moreover, Caselli et al. (2021) find that import competition from China reduced monopsony power of firms in France. Similar to these researches, the analysis in this paper also considers China's accession to WTO but studies the impact of China's integration to world trade on the behavior of Spanish exporting firms.

Additionally, Felix (2021) finds that trade liberalization raised Brazilian firms' labor market monopsony power through increased labor market concentration from 1990 to 1994. MacKenzie (2021) discovers that trade induced higher labor market power for large firms but lower for small firms in India for the years 2008-2009. This paper departs from these studies by analysing a longer period and examining the labor market outcomes of trade in a developed country. Finally, some researchers studied the implications of trade in the presence of monopsony power in labor markets (e.g. Macedoni and Tyazhelnikov, 2019; Jha and

[5]However, HHI is no longer used as an appropriate measure of market power in industrial organization literature. Labor economics literature recently adopted concentration ratios such as the HHI to identify employer's market power in labor market. These studies have been subject to criticisms because such measures can reflect product market power as well and they are considered to be endogenous market outcome (e.g. Berry et al., 2019; Syverson, 2019; Langella and Manning, 2021).

Rodriguez-Lopez, 2021; Egger et al., 2022; Méndez and Van Patten, 2022). However, this is a different strand of literature which does not investigate how trade affects monopsony power, but rather how trade affects wages and employment when the labor market is monopsonistic.

The rest of the paper is organized as follows. Section 4.2 introduces the model and discuss the channels that might have contributed to increase in monopsony power of exporting firms. Section 4.3 describes the dataset. Section 4.4 presents the empirical analysis whereas Section 4.4.1 estimates the wage and employment elasticities to exporting. Section 4.4.2, Section 4.4.3 and Section 4.4.4 examine and discuss various channels of the findings such as labor share, labor productivity and the demand for low-skill, high-skill and temporary workers. Section 4.5 concludes.

4.2 Theoretical Framework

This section presents a method to estimate the effects of firm behavior on its monopsony power, which is developed as an extension to the standard monopsony measure. I describe the differences and implications of the textbook model and my approach. I further discuss potential channels through which larger exports affect monopsony power because I employ this framework for exporting in the empirical analysis.

The standard model of monopsony in the literature of labor economics relies on estimating the labor supply elasticity. In recent years, a growing number of theoretical and empirical models have been developed to discover the presence of imperfectly competitive labor markets (e.g. Beaudry et al., 2018; Lamadon et al., 2022; Berger et al., 2022) but there is still a lack of a unified approach for the measurement of firms' monopsony power in labor markets (Langella and Manning, 2021).

In contrast to perfectly competitive labor markets that take the wage as given to the firm and defined as W, the wage is considered to be a function of employment in a monopsonistic environment and defined as $W(L)$. A monopsonist firm then chooses the level of employment to maximize its profits

$$\max_{L} \pi = R(L) - W(L)L \tag{4.1}$$

where $R(L)$ denotes the firm revenue, $W(L)$ denotes the firm's average wage and L denotes the number of workers employed at the firm. In equilibrium, the deviation of last hired worker's contribution to firm revenue (referred as marginal revenue product of labor) from wage becomes equal to the cost of hiring that last worker: $\partial R(L)/\partial L = \partial \Big(W(L)L \Big)/\partial L$. We then obtain

$$\frac{MRPL - W}{W} = \frac{1}{\varepsilon}, \tag{4.2}$$

where $MRPL = \partial R/\partial L$ denotes the marginal revenue product of labor and ε represents the labor supply elasticity. A monopsonist faces an upward-sloping supply curve and holds bargaining power to set the wage ($\varepsilon = \frac{\partial L}{\partial W}\frac{W}{L} > 0$).

I introduce a new framework that allows to measure how the firm behaviour changes its monopsony power in labor market. This method relies on nonrigid assumptions and the parameters to be estimated are integrated to the standard monopsony measure of labor supply elasticity. I start by using the level of exports as a demand shifter and assume that employment is a function of firm's exports denoted as E:

$$L(E). \tag{4.3}$$

E refers to export volumes rather than exporting status, i.e. exporting at the intensive margin. In this paper, I study exporting at the intensive margin but export status as the extensive margin of trade can also be the subject of a study.

The assumption above induces that exporting affects the level of labor demand. This is a realistic and reasonable definition because trade literature documents that expansion to new export markets allows exporters to boost their production and therefore employ more workers. Notice that this formulation is different because conventional approach shown in Equation (4.2) defines the employment as L and does not consider that a firm behavior might affect firm's employment decision.

In a perfectly competitive labor market, the demand shock to a firm should not affect wages because they are set at the market level. However, in a monopsonistic environment, wage is assumed to be the function of employment because the firm's demand for labor can affect the wages. Instead of assuming that labor demand determines the firm's wage, which leads to Equation (4.2), I assume that exporting (or any other firm activity) might also affect wage either directly through rent sharing due to the expansion of markets or indirectly through the changes in labor demand. Therefore, I define the wage as a function of both exporting and employment:

$$W\Big(E, L(E)\Big). \tag{4.4}$$

Consider a profit-maximizing firm choosing how much to export. The firm's problem is then given as

$$\max_{E} \pi = R\Big(L(E)\Big) - W\Big(E, L(E)\Big)L(E) \tag{4.5}$$

where $R\Big(L(E)\Big)$ denotes the firm's revenue. Revenue is a function of employment just as in the standard monopsony model but the difference in this setting is that revenue is also a function of exporting through employment. The first-order condition for a monopsonistic firm involved in exporting yields

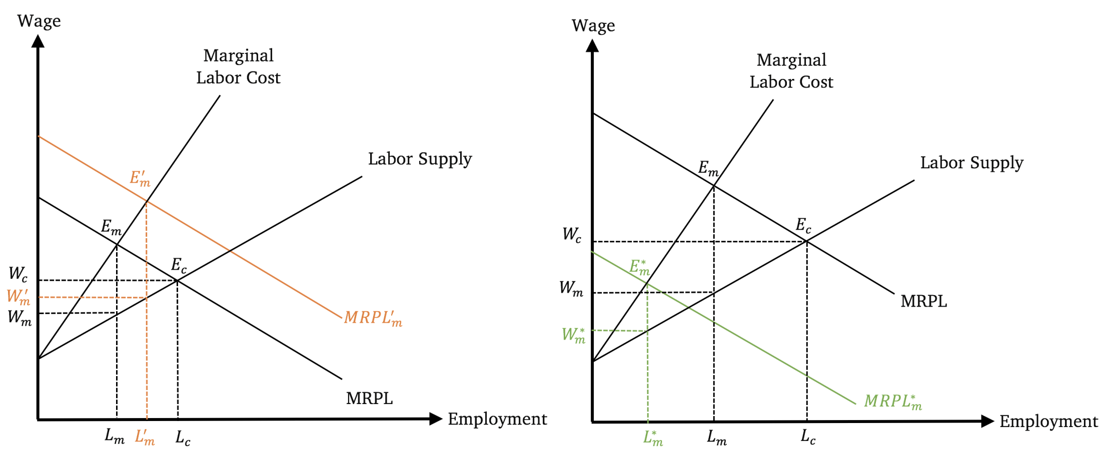
$$\frac{MRPL - W}{W} = \varepsilon^{-1} + \frac{\rho^W}{\rho^L} \tag{4.6}$$

where $\rho^W = \frac{\partial W/\partial E}{W/E}$ denotes the elasticity of wage to exporting and $\rho^L = \frac{\partial L/\partial E}{L/E}$ denotes the elasticity of employment to exporting. These elasticities must be appropriately estimated to measure the effects of the firm behaviour on monopsony power. The details of deriving Equation (4.6) are provided in the Appendix 4.A.2.

The equilibrium in Equation (4.6) is similar to the standard static monopsony measure expressed in Equation (4.2) but includes additional elasticities (ρ^W and ρ^L) representing the impacts of the choice variable on firms' monopsony power. The left hand side of the equation, which is identical to the conventional approach, shows how much wage deviates from marginal revenue product of labor in percentage level. In other words, it measures the difference between the last hired worker's contribution to revenue ($MRPL$) and firm's average wage paid (W). Larger this gap, less competitive the market is.

The right hand side of the Equation (4.6) includes several elasticities to be estimated. $\varepsilon > 0$ indicates that the firm has wage-setting power while $\varepsilon = 0$ suggests that the market is perfectly competitive. ρ^W measures to what extend exports affect firm's average wage. If the firm's exports do not affect its wage setting power directly or indirectly through the changes in labor demand, we have $\rho^W = 0$. On the other hand, ρ^L measures to what extend exports affect firm's employment and $\rho^L = 0$ implies that exports do not affect labor demand. In case of $\rho^W = 0$ or $\rho^L = 0$, the equilibrium boils down to the standard formula of monopsony power in Equation (4.2).

Figure 4.1 illustrates the effect of a firm's behavior on labor market monopsony power. The labor supply curve to an individual employer is upward-sloping. The left panel and the right panel depict how wage changes when labor demand increases and decreases for a monopsonist firm, respectively. The initial position of labor demand is labelled as $MRPL$. The intersection of $MRPL$ and Labor Supply curve is the competitive outcome denoted as E_c in which the competitive wage and employment are denoted as W_c and L_c, respectively. The point labelled as E_m is the monopsony equilibrium in which the monopsonist's labor demand and wage are respectively denoted as L_m and W_m. Notice that in both panels, wage and employment are lower in monopsony equilibrium than in perfectly competitive equilibrium, $W_m < W_c$ and $L_m < L_c$.



(a) Panel A. Positive Demand Shock **(b)** Panel B. Negative Demand Shock

Figure 4.1: Firm Behavior and Labor Market Monopsony
Note: $MRPL$ is the marginal revenue product of labor, W denotes the wage and L denotes the employment level. E represents the equilibrium point. Subscripts m and c refer to monopsony and competitive market equilibrium, respectively. Left panel depicts the case of positive demand shock while right panel shows the case of negative demand shock.

Suppose there is an increase in labor demand as shown on the left panel. $MRPL$ then shifts upward to $MRPL^{'}_{m}$ where equilibrium wage and employment respectively become $W^{'}_{m}$ and $L^{'}_{m}$. Wages increase with higher labor demand above W_m but still remain below competitive wage $W^{'}_{m} < W_c$. On the other hand, a decrease in labor demand induces a downward shift from $MRPL$ to $MRPL^{*}_{m}$ as demonstrated on the right panel. In this case, the firm reducing its labor demand to L_m^* lowers wages to the point W_m^*, below both competitive and monopsony equilibrium wage, W_c and W_m.

There may be two reasons of a shift in marginal revenue product of labor ($MRPL$) curve. On the one hand, technical change or quality upgrading might generate a positive demand shock and shift $MRPL$ curve upward by raising the appeal of the firm's product. In this case, the quantity of products sold might increase without any change in the price of the product, i.e. $\partial P/\partial L = 0$, therefore $MRPL = \partial R/\partial L = P\partial Q/\partial L$. In contrast, quality downgrading would generate a negative demand shock and shift $MRPL$ curve downwards by reducing the appeal of products to consumers. Alternatively, we can relax the assumption on perfectly competitive product markets and consider that the firm has a price setting power in product market such that $MRPL = \partial R/\partial L = \frac{\partial P}{\partial Q}\frac{\partial Q}{\partial L}Q + P\frac{\partial Q}{\partial L}$. In this scenario, $MRPL$ curve might move upward or downward because of the variations in price setting behavior or product quality related changes, or both.

Several mechanisms might explain the changes in the monopsony power of exporters. One possibility is through the variation in labor share. A robust evidence on the fall of labor share has been documented across countries and industries in recent years (e.g. Karabarbounis and Neiman, 2014; Grossman and Oberfield, 2022). Lower labor share indicates that workers receive smaller share of income generated in firm's revenue. In a monopsonistic labor market, labor share might fall if the firm does not raise wages proportionately in response to increased exports. Thus, firms might extract rents from exporting through market expansion and raise their bargaining power on their workforce. Furthermore, exporting might raise firm revenue, but not necessarily labor share, if the adoption of new technologies displace workers from the tasks they are performing.[6]

The rise in monopsony might also be related to labor productivity. A large body of literature documents that exporting tends to raise productivity through larger capital investments and the adoption of new technologies (e.g. Lileeva and Trefler, 2010; Bustos, 2011).[7] Theoretically, any firm-level characteristics including labor productivity should be irrelevant in determination of wages in a competitive market. However, Card et al. (2016) show that labor productivity measured

[6]For instance, Kline et al. (2019) find that productivity shocks generated from patenting increases revenue more than wages.

[7]See Bernard et al. (2007), Bernard et al. (2012), Melitz and Trefler (2012) and Shu and Steinwender (2019) for excellent reviews on the relevant literature and corresponding references.

as value-added per worker is significantly related to wages, which reflects an imperfectly functioning labor market. In fact, workers would have limited opportunities outside of their current job position if they become less productive and lose their bargaining power because their attractiveness to competitor firms, i.e. the outside job options, falls. Hence, firms might obtain higher (lower) monopsony power when workers are less (more) productive.[8]

The framework introduced in this paper allows to measure how firms' decisions affect their labor market monopsony power and highlights the role of demand shocks in monopsony power. In order to estimate the elasticities unbiasedly, the method requires only the data on firm's activity as a demand shifter (e.g. exports, imports, innovation, R&D expenditures), average wage and employment. While this approach can be used in various settings to investigate firm behavior in labor market monopsony, I implement it for Spanish manufacturing firms' exporting activity in this paper.[9] One caveat is that the researcher additionally needs to estimate labor supply elasticity as well to identify how much monopsony power changed, which requires to overcome endogeneity problem.

4.3 Data

In this section, I present the firm-level dataset used in the empirical analysis, reveal some descriptive facts on firms and provide some information on labor market conditions in Spain.

I use the Encuesta Sobre Estrategias Empresariales (ESEE) dataset, a firm-

[8]Note that there might be a reverse relationship between labor productivity and employers' monopsony power as well. For example, firms might have monopsony power and this might reduce the productivity of workforce. However, the direction of this relationship is not the subject of this study. In this paper, I analyse how trade affects monopsony power and test whether this is associate with workers' productivity to some extent.

[9]Trade induced changes in firms' demand for labor might depend on whether the firm operates in input or output markets as well as depending on the type of trade activity, importing or exporting. Shu and Steinwender (2019) highlight this point and reviews how trade affects output producers (import competition and larger export markets in output markets) and input producers (import competition in input markets and larger input import opportunities). While the framework introduced here can allow to incorporate such details, I do not analyse inputs and output markets separately because of data restrictions.

level data provided by the SEPI foundation in Madrid. The ESEE is a manufacturing sector representative panel dataset comprised of around 2000 firms with 10 or more employees surveyed every year. Appendix 4.A.3 presents the list of variables used in the analysis and their codes in the dataset. The data distinguish 20 different industries at the two-digit level of NACE classification and 17 regions of NUTS2 classification. I use industry-level price indices to deflate firm-level variables obtained from the Spanish Statistical Office (Instituto Nacional de Estadistica, INE).

The approach I introduce relies on estimating wage and employment elasticities to a firm behavior. For measuring the elasticities, ρ^W and ρ^L, I primarily need information on average wage, employment and export level, which I observe in my dataset. I also obtain substantial amount of details on employment of low-skill, high-skill and temporary workers. All these variables allow me to investigate the channels that might have contributed to the changes in monopsony power, making this dataset suitable to estimate the effects of exporting on firms' labor market monopsony power.

Table 4.1 presents summary statistics of variables used in the analysis for the period before and after China's accession to WTO, i.e. 1996-2001 and 2002-2007. Labor share is reported in percentage level and all the other variables are in natural logarithm. Wage, labor productivity, high-skill workers and labor costs are higher after 2001. Moreover, exports, imports, domestic sales and value-added are also higher on average between 2002 and 2007. Employment, low-skill workers, temporary workers, labor share and capital investments have lower mean values during the 2002-2007 period compared to China's pre-accesion period.

In the empirical analysis, I focus on exporting at the intensive margin and restrict the sample to firms involved in exporting activity. The reason of this choice is that I want to identify the within-firm effects of exporting at various intensities rather than the impact of entry to or exit from export markets on employees. The changes at the extensive margin have significant implications on general equilibrium outcomes and would require considering the reallocation of resources, which is not the subject of this paper. However, the method allows to examine the exporting status as well as other firm behaviors.

Figure 4.2 depicts the relationship between wage and exports on the left panel and the relationship between employment and exports on the right panel. It is evidently seen that the slope of the graph on the left panel is flat, suggesting that wage is rigid and does not change much with considerably higher export levels.

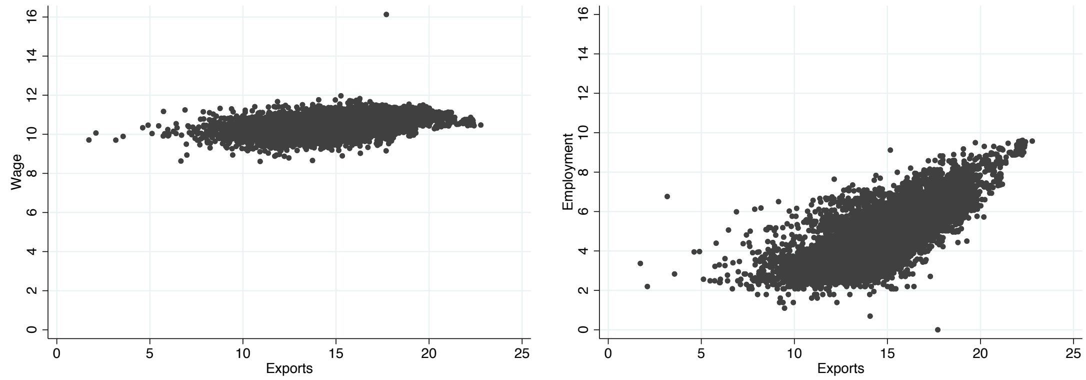
Table 4.1: Summary Statistics

	1996-2001			2002-2007		
	Mean	SD	Obs.	Mean	SD	Obs.
Exports	15.480	2.442	5283	15.521	2.518	5014
Wage	10.463	0.426	5283	10.534	0.368	5014
Employment	5.160	1.353	5283	5.139	1.334	5014
Labor share	0.217	0.147	5283	0.213	0.117	5014
Labor productivity	10.909	0.648	5222	10.938	0.649	5002
High-skill workers	2.610	1.674	5205	2.784	1.666	4965
Low-skill workers	5.771	1.337	5205	5.738	1.316	4965
Temporary workers	3.206	1.880	5283	2.952	2.030	5014
Imports	14.792	2.520	5283	14.879	2.542	5014
Domestic sales	16.779	1.787	5283	16.816	1.763	5014
Capital investments	13.589	2.131	5283	13.440	2.215	5014
Labor costs	15.624	1.575	5283	15.673	1.522	5014
Value-added	16.069	1.655	5222	16.077	1.626	5002

Notes: The table presents the summary statistics for exporters for the periods 1996-2001 (before China's accession to WTO) and 2002-2007 (after China's accession to WTO). Mean values, standard deviations and the number of observations for the variables used in the analysis are reported. Exports, Wage, Employment, Labor productivity, High-skill workers, Low-skill workers, Temporary workers, Imports, Domestic sales, Capital investments, Labor costs and Value-added are in logs. Labor share is given in percentage and defined as the share of total labor costs in firm revenue. Wage is defined as the average wage paid to workers in a given year. Labor productivity is defined as value-added per worker. Labor costs represent the total wage paid to the workers in a given year.

On the right panel, the slope of the graph is much steeper, indicating that labor demand is monotonically increasing in exports. These plots show the underlying mechanism in the empirical analysis in which labor demand is more responsive to exports than wages.

Spain has chronic labor market problems documented in various studies. Vacancy rate has been declining and unemployment rate has been increasing during the 2000s (OECD, 2014). In comparison to other EU countries, unemployment rate has been higher and more volatile for decades (Dolado et al., 2021). Youth employment is low and the youth to adult unemployment ratio is high (Dolado, 2017). Moreover, firing costs are high due to severance pay, notice periods and



(a) Panel A. Wage-Exports Relationship **(b)** Panel B. Employment-Exports Relationship

Figure 4.2: Wages, Employment and Exports
Note: The figures show the wage-exports relationship on the left panel and employment-exports relationship on the right panel for the 1996-2007 period. Wage denotes the annually paid average firm-level wage per worker. Employment denotes the total number of workers employed annually at the firm in logs. Exports denotes the annual value of exports of the firm. All variables are in natural logarithm.

court procedures (Bentolila et al., 2012).

Mobility restrictions is one of the main reasons of increased monopsony power as originally analysed in Robinson (1933).[10] In Spain, potential job opportunities of workers are restricted because geographical mobility is very low (OECD, 2005; Vandenbrande et al., 2006). Finally, according to the OECD database, collective bargaining coverage in Spain has considerably declined from 84.8% in 2000 to 76.5% in 2006.[11] All these statistics point out considerable labor market frictions in Spain and I continue with a more detailed analysis in the next section to provide robust evidence on labor market monopsony.

[10] Robinson (1933) considered a single firm in a town to explain monopsony power. She assumed that many workers compete for jobs offered by a single employer in which the lack of outside options in and outside the town due to mobility restrictions increases the bargaining power of the single employer and give monopsony power.

[11] The data are obtained from `https://stats.oecd.org/Index.aspx?DataSetCode=CBC`

4.4 Empirical Analysis

I want to examine whether more intensely exporting firms increased their labor market power from 1996 to 2007. All of my estimations employ difference-in-differences approach and compare the impact of exporting on labor market outcomes before and after China's accession to WTO. In Section 4.4.1, I introduce the empirical model and estimate the wage and employment elasticities to exporting. After identifying the parameter estimates, I investigate the changes in labor share in Section 4.4.2, labor productivity in Section 4.4.3 and skill demand and temporary workers in Section 4.4.4.

4.4.1 Wage and Employment Elasticities

In this section, I estimate the wage and employment elasticities to exporting, ρ^W and ρ^L respectively demonstrated in Equation (4.6). The estimations compare the impact of exporting on wage and employment before and after China's accession to World Trade Organization (WTO).

To obtain the elasticity of wage to exporting, I estimate the following equation:

$$\begin{aligned}\log\left(W_{ijt}\right) = \alpha_i^W + \beta^W \log\left(E_{ijt}\right) + \rho^W * WTO * \log\left(E_{ijt}\right) \\ + \phi \log\left(L_{ijt}\right) + \gamma X'_{ijt} + \mu_{jt} + \delta_{rt} + \varepsilon_{ijt}^W,\end{aligned} \tag{4.7}$$

where i denotes the firm, j denotes the industry, r denotes the region that the firm is located and t denotes the year. W_{ijt} represents the firm-level average wage and E_{ijt} represents the value of firm exports. To find the elasticity of employment to exporting, I estimate the following model:

$$\log\left(L_{ijt}\right) = \alpha_i^L + \beta^L \log\left(E_{ijt}\right) + \rho^L * WTO * \log\left(E_{ijt}\right) + \eta X'_{ijt} + \mu_{jt} + \delta_{rt} + \varepsilon_{ijt}^L, \tag{4.8}$$

where L_{ijt} denotes the number of employees. I define WTO as a binary variable equal to 1 from the year 2002 to 2006 and equal to 0 from 1996 to 2001. ε_{ijt}^W and ε_{ijt}^L are the error terms. I cluster the standard errors at the firm-level because the main explanatory variable is measured at the firm-level. The model in Equation (4.7) includes L as a control variable because wage is assumed to be a function of exporting and employment as shown in Equation (4.6).

The main variables of interest are the interaction terms. I argue that exporting in Spain after China's accession to WTO in 2001 has differential effects on labor market outcomes at the firm level, conditional on covariates. Respectively, ρ^W and ρ^L establish how increased exports after 2001 affected wages and labor demand.

These specifications are perhaps not free of endogeneity problems and I control for various covariates to reduce potential omitted variable bias. Some firms might have better negotiating skills for wage setting or human resources management. To control for such unobserved firm characteristics, I incorporate firm fixed-effects α_i^W in Equation (4.7) and α_i^L in Equation (4.8).

Notice that time-varying idiosyncratic demand shocks cannot be captured by firm fixed effects. For instance, the accession of China to WTO might have increased firms' access to cheaper intermediate imports and Spanish firms might have then more easily imported cheaper intermediate inputs with China's integration to international markets (e.g. Amiti and Konings, 2007). Firms might have also increased capital investments because of the expansion of market size (e.g. Lileeva and Trefler, 2010; Bustos, 2011). On the other hand, offshoring some of the production processes to China might have affected wages as well as employment (e.g. Hummels et al., 2018). Finally, domestic sales of firms might have declined due to import competition from China after 2001 and negative demand shocks might have reduced wages and employment. Thus, I control for firm-level covariates such as imports, domestic sales and capital investments denotes as X'_{ijt}.

I condition on a set of fixed effects to control for sectoral and regional developments. First, I include industry-year pair fixed-effects μ_{jt}. These take into account the sectoral shocks such as import competition from China, industry specific technological and regulatory changes. I further control for region-year fixed effects denoted as δ_{rt}. They accommodate the possibility that tougher international markets affected more intensely exporting firms differentially across regions.

The results from estimating Equation (4.7) and (4.8) are shown in Table 4.2. Panel A presents the elasticity for wage (ρ^W) and Panel B presents the elasticity for employment (ρ^L). Column 1 shows the results with firm fixed effects. Increased exporting has a significant positive impact on wages and employment in normal times but the magnitude for employment (0.0821) is higher than for wage (0.0279). Higher exports induce larger increase in employment than in wages, which is consistent with the sharper curve employment-exports relationship and flatter curve wage-exports relationship in Figure 4.2. However, in the period after 2001, this positive impact was reversed and the impact of exporting on wage and

Table 4.2: Wage and Employment Elasticities of Exporting 1996-2007

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ρ^W						
WTO*Exports	-0.0119***	-0.0118***	-0.00910***	-0.0113***	-0.00901***	-0.00890***
	(0.00226)	(0.00217)	(0.00231)	(0.00219)	(0.00225)	(0.00214)
WTO	0.297***	0.289***				
	(0.0375)	(0.0359)				
Employment	-0.162***	-0.240***	-0.174***	-0.175***	-0.172***	-0.240***
	(0.0202)	(0.0230)	(0.0206)	(0.0201)	(0.0200)	(0.0224)
Exports	0.0279***	0.0318***	0.0209***	0.0238***	0.0207***	0.0256***
	(0.00387)	(0.00390)	(0.00350)	(0.00376)	(0.00347)	(0.00356)
Imports		0.00665***				0.00383*
		(0.00241)				(0.00208)
Domestic Sales		0.0788***				0.0717***
		(0.0124)				(0.0112)
Capital Investment		0.00772***				0.00689***
		(0.00200)				(0.00189)
Observations	9963	9963	9963	9962	9962	9962
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FEs	No	No	Yes	No	Yes	Yes
Region-year FEs	No	No	No	Yes	Yes	Yes
R-squared	0.910	0.917	0.926	0.918	0.928	0.933
Panel B: ρ^L						
WTO*Exports	-0.0120***	-0.00972**	-0.0120***	-0.0113**	-0.0119**	-0.00968**
	(0.00429)	(0.00377)	(0.00466)	(0.00448)	(0.00469)	(0.00414)
WTO	0.227***	0.172***				
	(0.0697)	(0.0611)				
Exports	0.0821***	0.0721***	0.0775***	0.0792***	0.0781***	0.0718***
	(0.00773)	(0.00630)	(0.00798)	(0.00802)	(0.00815)	(0.00678)
Imports		0.0245***				0.0235***
		(0.00494)				(0.00483)
Domestic Sales		0.171***				0.171***
		(0.0227)				(0.0217)
Capital Investment		0.0313***				0.0308***
		(0.00368)				(0.00359)
Observations	9963	9963	9963	9962	9962	9962
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FEs	No	No	Yes	No	Yes	Yes
Region-year FEs	No	No	No	Yes	Yes	Yes
R-squared	0.978	0.982	0.979	0.979	0.980	0.983

Notes: The table reports the elasticities of wage and employment to exporting. Dependent variable is the natural logarithm of firm-level average wage in Panel A, which presents the wage elasticity denoted as ρ^W. Dependent variable is the natural logarithm of firm's total employment in Panel B, which presents the employment elasticity denoted as ρ^L. WTO is a dummy variable equal to 1 for the period 2002-2007 and 0 for the period 1996-2001. Explanatory variables Employment, Exports, Imports, Domestic Sales and Capital Investments are in logs. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

employment became significantly negative, i.e. the accession of China to WTO had negative impact of exporting firms on firm-level labor market outcomes. Column 2 includes firm-level covariates. The magnitudes change slightly but they all remain significant at 1% level.

Columns 3-6 show the results with the inclusion of industry-year and region-year fixed effects. My preferred specification is presented in Column 6 that incorporates time-varying sectoral and regional controls as well as firm-level imports, domestic sales and capital investments. The elasticities are stable across estimations and the results are robust to the inclusion of full set of control variables.

According to Equation (4.6), the ratio of wage and employment elasticities approximately corresponds to 0.92 ($-0.00890/-0.00968$). Sokolova and Sorensen (2021) collect the mean and median values of labor supply elasticity estimates for Europe documented in the literature. They report that the median estimate is 1.49, which induces that firms pay their employees 60% of marginal revenue product,[12] and the mean estimate is 6.96, which induces that firms pay their employees 88% of marginal revenue product.[13] I take these mean and median estimates as a rough measure for labor supply elasticity and plug it into Equation (4.6) to obtain the effect of exporting on monopsony power. These computations suggest that when we consider the impact of exporting on monopsony, workers are paid in a range of 39-49% of their marginal revenue product,[14] which implies a 36-45% decrease in workers' pay, i.e. increase in monopsony power due to exporting.[15]

4.4.2 The Impact of Trade on Labor Share

As discussed in Section 4.2, rising monopsony power might be associated with the fall in labor share. A growing body of literature relates the decline in labor share to imperfections in product markets, largely through the rise of superstar firms (e.g. Autor et al., 2020; Barkai, 2020). In this context, the decline in labor share might arise from higher markups (charging higher price) without any change in labor market conditions. However, monopsonistic competition in labor markets

[12]This can be obtained from $W = 100/(1/1.49 + 1) = 60$.

[13]This can be obtained from $W = 100/(1/6.96 + 1) = 88$.

[14]This can be obtained from $W = 100/(1/1.49+0.92+1) = 39$ and $W = 100/(1/6.96+0.92 + 1) = 49$.

[15]This can be obtained from $(39 - 60)/60 = -36\%$ and $(49 - 88)/88 = -45\%$.

has a potential to explain recently documented fall in labor share (e.g. Brooks et al., 2021; Gouin-Bonenfant, 2022).[16]

I estimate the model using labor share in revenue as the outcome variable. I must emphasize that, rather than asserting any causal relationship between monopsony power and labor share, I investigate how exports affected labor share and evaluate whether the exports induced increase in monopsony power after 2001 is reconciled with the fall in labor share.

Table 4.3: The Impact of Exporting on Labor Share, 1996-2007

	(1)	(2)	(3)	(4)	(5)	(6)
WTO*Exports	-0.00407***	-0.00452***	-0.00205*	-0.00355***	-0.00193*	-0.00232**
	(0.000797)	(0.000744)	(0.00108)	(0.000842)	(0.00110)	(0.00108)
WTO	0.0679***	0.0802***				
	(0.0133)	(0.0125)				
Exports	-0.0138***	-0.0129***	-0.0141***	-0.0135***	-0.0142***	-0.0137***
	(0.00395)	(0.00441)	(0.00399)	(0.00368)	(0.00392)	(0.00429)
Imports		-0.00387**				-0.00423***
		(0.00164)				(0.00150)
Domestic Sales		-0.0373***				-0.0322***
		(0.00762)				(0.00769)
Capital Investment		0.000650				0.000576
		(0.00167)				(0.00158)
Observations	9963	9963	9963	9962	9962	9962
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FEs	No	No	Yes	No	Yes	Yes
Region-year FEs	No	No	No	Yes	Yes	Yes
R-squared	0.695	0.710	0.715	0.712	0.727	0.737

Notes: This table presents the estimation results for the relationship between labor share and exporting. Dependent variable is labor share defined as the ratio of labor costs to firm revenue. WTO is a dummy variable equal to 1 for the period 2002-2007 and 0 for the period 1996-2001. Explanatory variables Employment, Exports, Imports, Domestic Sales and Capital Investments are in logs. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

The regression results are reported in Table 4.3. Columns 1 (without firm-level controls) and 2 (with firm-level controls) show that during the period of China's increasing prevalence in international trade from 2002 to 2007, labor share in Spanish manufacturing industries increased by 6.7%. Moreover, 1% increase in exports merely reduced labor share by around 0.013 unit. The coefficient estimate

[16] Grossman and Oberfield (2022) and Manning (2021) reviews the literature on how labor share might be related to monopsony power.

on the interaction term is negative, significant at the 1% level but smaller in magnitude than the coefficient on exports. Therefore, exporting reduced labor share between 1996 and 2007 but the fall was greater before 2001 than after 2001.

To understand the decline in labor share, I estimate the model using the two components of labor share, labor costs and sales (firm revenue), as the dependent variables separately. Table C1 in Appendix 4.A.1 presents the results for labor costs in Panel A and for sales in Panel B. Positive and significant coefficients on WTO and Exports suggest that labor costs increased after China's accession to WTO for all firms while more intensely exporting raised the labor costs during the overall sample period of 1996-2007. However, as evidently shown in all specifications of Panel A, the coefficient estimate on the interaction term with significantly negative sign indicates that higher exports particularly after 2001 reduced labor costs of firms. In contrast, larger volume of exports during the 2002-2007 period did not reduce sales as in labor costs. Hence, we can conclude that the decline in labor share despite magnified exports after 2001 was due to the fall in labor costs while larger exports did not affect firm sales.

The estimations are robust to controlling for industry-year and region-year fixed effects, time-invariant firm characteristics and firm-level demand shocks. These findings suggest that larger exports reduced labor share in revenue but the fall in labor share has been milder after 2001. Aligned with the findings in previous studies, the rise in monopsony power appears to be related to the decline in labor share.

4.4.3 Productivity and Monopsony

Previously in Section 4.2, I discussed the potential channel that the fall in productivity might have contributed to rising monopsony power. To analyse whether firms' exports after China's entry to WTO induced a fall in labor productivity in parallel with the increases in monopsony power, I use value-added per worker as a measure of labor productivity. The results are presented in Table 4.4.

Column 1 shows the results of difference-in-differences estimates. Larger exports are positively and significantly related to labor productivity while labor productivity within firms increased after China's integration to world markets. However, exports after 2001 are negatively associated with labor productivity. The inclusion of firm-level controls (in Column 2) slightly reduces the magnitude of the additional significant impact after 2001 for exporters and for all firms on

Table 4.4: The Impact of Exporting on Labor Productivity, 1996-2007

	(1)	(2)	(3)	(4)	(5)	(6)
WTO*Exports	-0.0141***	-0.0120**	-0.0147**	-0.0139***	-0.0159***	-0.0143**
	(0.00518)	(0.00515)	(0.00577)	(0.00523)	(0.00598)	(0.00592)
WTO	0.238***	0.190**				
	(0.0807)	(0.0805)				
Exports	0.0487***	0.0538***	0.0477***	0.0471***	0.0470***	0.0551***
	(0.00791)	(0.00792)	(0.00796)	(0.00787)	(0.00794)	(0.00804)
Imports		-0.0124**				-0.0122**
		(0.00572)				(0.00603)
Domestic Sales		0.144***				0.146***
		(0.0260)				(0.0292)
Capital Investment		-0.00321				-0.00513
		(0.00562)				(0.00560)
Observations	9892	9892	9892	9891	8922	8922
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FEs	No	No	Yes	No	Yes	Yes
Region-year FEs	No	No	No	Yes	Yes	Yes
R-squared	0.711	0.720	0.721	0.720	0.733	0.740

Notes: This table reports the effects of exporting on labor productivity. Dependent variable is the natural logarithm of labor productivity. WTO is a dummy variable equal to 1 for the period 2002-2007 and 0 for the period 1996-2001. Explanatory variables Employment, Exports, Imports, Domestic Sales and Capital Investments are in logs. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

average, but raises the overall magnitude of exporting on labor productivity. From 2002 to 2007, Spanish manufacturing firms experienced 19% increase in labor productivity even though exporting firms experienced a decline in labor productivity.

In Columns 3-6, I drop dummy variable for the period 2002-2007 and control for industry-year and region-year fixed effects. The coefficient estimate on exports remain significant and I find that every 1% increase in firm exports is associated with 0.05% higher labor productivity on average. The coefficient estimate on the interaction term remains statistically significant at the 5% level and negative. With China's accession to WTO, 1% increase in firm exports after 2001 induced a 0.0143% decline in labor productivity. Hence, sectoral and regional developments are not the main determinants of the negative impact of exports on labor productivity after China's integration to international markets in 2001.

Recall that labor productivity is defined as value-added per worker. Therefore, a fall in labor productivity might be due to the changes in value-added, in number of workers or both. I estimate the model by using value-added as a dependent variable to reveal what has been driving the the results. Table C2 in Appendix 4.A.1 reports the regression results.

In all specifications, the coefficients on the interaction term are negative and significant at the 1% level. The magnitude of coefficient estimates are in a range of -0.021 and -0.026 and smaller than the employment elasticity that vary within the range of -0.009 and -0.01 presented in Table 4.2. Hence, the findings suggest that the fall in labor productivity seems to be because of larger decline in value-added than in number of workers.

In the estimations, I find that more intensely exporting decreased labor productivity for the 2002-2007 period even though higher exports are positively associated with labor productivity from 1996 to 2007.[17] Lower productivity of Spanish manufacturing firms after China's accession to WTO might explain the increased monopsony power of exporters because the fall in labor productivity would reduce the outside option of workers, as discussed in Section 4.2.

4.4.4 Skill Demand and Temporary Workers

The effects of trade activities may be more pronounced for more skill-intensive firms (e.g. Kondo et al., 2022). For instance, exporting may require the performance of different tasks in the production through the reallocation of capital and product mix. More specifically, exporting firms might utilize better technologies (e.g. Lileeva and Trefler, 2010; Bustos, 2011), produce different products (e.g. Bernard et al., 2011; Mayer et al., 2021) and demand more skilled workers (e.g. Bustos, 2005; Brambilla et al., 2012). Hence, firms might have reduced their relative demand for low-skill workers with respect to high-skill workers, which might reflect the reduced bargaining power of firms.

To examine whether larger export volumes raised monopsony power through the changes in skill composition, I use the IHS transformed values of high-skill and low-skill workers as the outcome variables in the model.[18] Table 4.5 presents the results where the dependent variable is high-skill workers in Panel A and low-skill

[17] This finding is somewhat consistent with several previous studies which documented that TFP in Spain has been declining steadily from 1990 until the Great Recession (e.g. Dolado, 2017; García-Santana et al., 2020).

[18] IHS (Inverse Hyperbolic Sine) is a commonly used approximation of the logarithm. In the sample, there are many observations with values between zero and one. IHS transformation allows to keep them in the analysis.

Table 4.5: Exporting, High-Skilled and Low-Skilled Workers, 1996-2007

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High-skilled Workers						
WTO*Exports	-0.00131	0.000422	-0.00534	-0.00145	-0.00678	-0.00557
	(0.00797)	(0.00791)	(0.00935)	(0.00853)	(0.00963)	(0.00956)
WTO	0.257**	0.212*				
	(0.127)	(0.126)				
Exports	0.0720***	0.0619***	0.0537***	0.0546***	0.0514***	0.0503***
	(0.0111)	(0.0105)	(0.0109)	(0.0112)	(0.0109)	(0.0107)
Imports		0.0260***				0.0105
		(0.00884)				(0.00873)
Domestic sales		0.152***				0.133***
		(0.0268)				(0.0258)
Capital Investment		0.0288***				0.0238***
		(0.00635)				(0.00659)
Observations	9840	9840	9840	9839	8866	8866
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FEs	No	No	Yes	No	Yes	Yes
Region-year FEs	No	No	No	Yes	Yes	Yes
R-squared	0.934	0.936	0.939	0.938	0.942	0.944
Panel B: Low-skilled Workers						
WTO*Exports	-0.0122***	-0.0103**	-0.0113**	-0.0116**	-0.0103**	-0.00895**
	(0.00449)	(0.00401)	(0.00496)	(0.00469)	(0.00494)	(0.00451)
WTO	0.218***	0.168***				
	(0.0729)	(0.0647)				
Exports	0.0801***	0.0701***	0.0762***	0.0775***	0.0713***	0.0667***
	(0.00748)	(0.00613)	(0.00773)	(0.00769)	(0.00775)	(0.00676)
Imports		0.0247***				0.0245***
		(0.00503)				(0.00515)
Domestic Sales		0.166***				0.164***
		(0.0218)				(0.0226)
Capital Investment		0.0311***				0.0288***
		(0.00371)				(0.00358)
Observations	9840	9840	9840	9839	8866	8866
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FEs	No	No	Yes	No	Yes	Yes
Region-year FEs	No	No	No	Yes	Yes	Yes
R-squared	0.977	0.981	0.978	0.977	0.979	0.983

Notes: This table reports the effects of exporting on high-skill and low-skill workers. Dependent variable is the IHS transformed values of high-skilled and low-skilled workers in Panel A and Panel B, respectively. WTO is a dummy variable equal to 1 for the period 2002-2007 and 0 for the period 1996-2001. The remaning explanatory variables Exports, Imports, Domestic Sales, Capital Investments are in logs. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

workers in Panel B.

The estimated coefficient on exports is positive and significant at the 1% level in all specifications of Panel A. This finding is aligned with the previous literature that larger exports raise the demand for skilled workforce. However, the coefficient on the interaction term is not significant in any specification, indicating that exports did not affect the demand for high-skill workers for the 2002-2007 period. Furthermore, the results in Panel B show that while more intensely exporting firms employed more low-skill workers over the 1996-2007 period, larger export volumes after China's accession to WTO in 2001 reduced the demand for low-skill workers. The coefficient on the interaction term is statistically significant at the 1% level in Column (1) and significant at the 5% level in Columns (2) and (6) which incorporates the full set of covariates.

On the other hand, empirical evidences suggest that a considerable share of Spanish employers carry out temporary contracts (Dolado et al., 2021). The share of temporary contracts has been increasing steadily from 2002 to 2006 (Sanz-de Galdeano and Terskaya, 2020) and Spain had one of the highest share of temporary employment in total employees among the OECD countries in 2007 (OECD, 2014). While restrictions on temporary contracts are not rigid due to the lack of monitoring by authorities (Bentolila et al., 2012), around 90% of entries to labor market are based on temporary contracts with very short job duration and only 3.5% of temporary job contracts have converted to permanent job contracts between 2002 and 2010 (Cahuc et al., 2016). In the 2000s, around 70% of Spanish firms reported that they dismissed mostly temporary workers in response to demand shocks (OECD, 2014).[19] In fact, government regulations aimed to increase labor market flexibility and reduce chronic unemployment problem by facilitating temporary contracts, therefore institutional settings must have played an important role in causing such disruptions in labor market.

In Table 4.6, I report the results from estimating the model using temporary workers as a dependent variable. In Column (1) and (2), the estimated coefficient on the interaction term is positive and significant at the 1% level. However, I lose the significance on the coefficient of interest once I control for time-varying industry characteristics as shown in Column (3). When I control for regional developments over time, the coefficient estimate remains statistically significant

[19]This figure is considered to be very high compared to roughly 40% in other European countries.

Table 4.6: The Effects of Exporting on Temporary Workers, 1996-2007

	(1)	(2)	(3)	(4)	(5)	(6)
WTO*Exports	0.0469***	0.0503***	0.0152	0.0375**	0.0118	0.0149
	(0.0172)	(0.0170)	(0.0184)	(0.0183)	(0.0191)	(0.0188)
WTO	-1.047***	-1.108***				
	(0.267)	(0.263)				
Exports	0.0542**	0.0416*	0.0759***	0.0699***	0.0784***	0.0664***
	(0.0221)	(0.0214)	(0.0223)	(0.0231)	(0.0230)	(0.0224)
Imports		0.00714				0.0231
		(0.0172)				(0.0182)
Domestic Sales		0.207***				0.214***
		(0.0441)				(0.0465)
Capital Investment		0.0999***				0.0974***
		(0.0146)				(0.0151)
Observations	9963	9963	9963	9962	9962	9962
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FEs	No	No	Yes	No	Yes	Yes
Region-year FEs	No	No	No	Yes	Yes	Yes
R-squared	0.755	0.760	0.766	0.763	0.773	0.777

Notes: This table reports the effects of exporting and importing on temporary workers. Dependent variable is logged temporary workers employed by the firm. WTO is a dummy variable equal to 1 for the period 2002-2007 and 0 for the period 1996-2001. The remaning explanatory variables Exports, Imports, Domestic Sales, Capital Investments are in logs. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

at the 5% level but smaller in magnitude. The results suggest that larger exports raised the demand for temporary workers after 2001 but such increases were driven by time varying industry factors.

4.5 Conclusion

How does exporting affect monopsony power in labor markets? In this paper, I examine the impact of exports on labor market monopsony power using a firm-level dataset. I develop a new method to estimate the effects of a firm behavior on monopsony power. My approach can be easily used in various settings and requires to have firm-level data on employment and wage for estimating the elasticities without relying on strong assumptions.

I rely on my empirical framework to analyse the impact of China's accession to WTO on Spanish exporters' labor market monopsony power. Empirical results show that more intensely exporting firms decreased the workers' pay by 36-45%

from 1996 to 2007 and they paid their workers 39-49% of their marginal revenue product. The findings reveal that larger exports led to a deviation from perfectly competitive environment in labor markets and raised the monopsony power of Spanish manufacturing firms.

In parallel with the increases in monopsony power between 1996 and 2007, I find a decline in labor share and labor productivity. These findings are consistent with recent evidences that relate rising market power firms to the fall in labor share (e.g. Autor et al., 2020) as well as the changes in labor productivity to wages (e.g. Card et al., 2016). The findings also reveal that after China's accession to WTO in 2001, larger exports reduced the employment of low-skilled workers but did not affect the demand for high-skill workers within firms and raised the number of temporary workers in some industries.

To assess its suitability, the proposed framework can be used for studying various firm behaviors apart from exporting such as extensive margins of trade, importing, R&D investing or innovation. Researchers might then identify what kind of firm activities can affect labor market monopsony power and whether they increase or decrease employers' bargaining power. On the other hand, exporters in different countries can be examined with this method. Considering a limited but a growing evidence on trade induced monopsony power, the future research can study how exporting (both at the intensive and extensive margins) affects labor market monopsony power of firms in other countries using a different dataset to evaluate external validity of the findings.

Trade induced labor market monopsony might induce large welfare losses through the misallocation of labor and have profound implications for trade policies. Therefore, identifying the conditions and factors in which trade can affect labor market monopsony power of firms may incline policymakers to reconsider the changes in trade relations and current labor laws. The findings in this paper provide robust evidences on rising trade induced labor market monopsony power, highlight the need for additional public policies to address monopsony and correct such market failures.

4.A Appendices to Chapter 4

4.A.1 Appendix Tables

Table C1: Exporting, Labor Costs and Sales (1996-2007)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Labor Costs						
WTO*Exports	-0.0219***	-0.0192***	-0.0190***	-0.0206***	-0.0173***	-0.0153***
	(0.00430)	(0.00362)	(0.00454)	(0.00439)	(0.00442)	(0.00378)
WTO	0.487***	0.420***				
	(0.0702)	(0.0588)				
Exports	0.0967***	0.0865***	0.0850***	0.0892***	0.0794***	0.0757***
	(0.00836)	(0.00671)	(0.00812)	(0.00849)	(0.00823)	(0.00691)
Imports		0.0253***				0.0228***
		(0.00507)				(0.00488)
Domestic Sales		0.209***				0.200***
		(0.0261)				(0.0266)
Capital Investment		0.0315***				0.0285***
		(0.00378)				(0.00363)
Observations	9963	9963	9963	9962	8989	8989
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FEs	No	No	Yes	No	Yes	Yes
Region-year FEs	No	No	No	Yes	Yes	Yes
R-squared	0.983	0.987	0.984	0.984	0.986	0.989
Panel B: Sales						
WTO*Exports	-0.00177	0.00261	-0.00623	-0.00195	-0.00625	-0.00300
	(0.00522)	(0.00378)	(0.00554)	(0.00523)	(0.00535)	(0.00399)
WTO	0.160*	0.0478				
	(0.0848)	(0.0623)				
Exports	0.137***	0.121***	0.126***	0.128***	0.119***	0.113***
	(0.0111)	(0.00832)	(0.0106)	(0.0109)	(0.0106)	(0.00851)
Imports		0.0477***				0.0431***
		(0.00653)				(0.00617)
Domestic Sales		0.345***				0.327***
		(0.0420)				(0.0442)
Capital Investment		0.0299***				0.0277***
		(0.00386)				(0.00361)
Observations	9963	9963	9963	9962	8989	8989
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FEs	No	No	Yes	No	Yes	Yes
Region-year FEs	No	No	No	Yes	Yes	Yes
R-squared	0.980	0.989	0.982	0.981	0.983	0.991

Notes: This table reports the effects of exporting on labor costs and sales. In Panel A, dependent variable is the log of total labor costs. In Panel B, dependent variable is the log of firm sales. WTO is a dummy variable equal to 1 for the period 2002-2007 and 0 for the period 1996-2001. The remaning explanatory variables Exports, Imports, Domestic Sales, Capital Investments are in logs. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

Table C2: Exporting and Value-Added (1996-2007)

	(1)	(2)	(3)	(4)	(5)	(6)
WTO*Exports	-0.0260***	-0.0215***	-0.0267***	-0.0253***	-0.0265***	-0.0231***
	(0.00617)	(0.00554)	(0.00687)	(0.00630)	(0.00687)	(0.00618)
WTO	0.464***	0.358***				
	(0.0977)	(0.0874)				
Exports	0.131***	0.127***	0.126***	0.127***	0.121***	0.124***
	(0.0115)	(0.00980)	(0.0115)	(0.0117)	(0.0116)	(0.0102)
Imports		0.0124*				0.0114
		(0.00735)				(0.00754)
Domestic Sales		0.317***				0.316***
		(0.0443)				(0.0485)
Capital Investment		0.0287***				0.0243***
		(0.00620)				(0.00603)
Observations	9899	9899	9899	9898	8929	8929
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FEs	No	No	Yes	No	Yes	Yes
Region-year FEs	No	No	No	Yes	Yes	Yes

Notes: This table reports the effects of exporting on value-added. WTO is a dummy variable equal to 1 for the period 2002-2007 and 0 for the period 1996-2001. The remaning explanatory variables Exports, Imports, Domestic Sales, Capital Investments are in logs. Standard errors are clustered at the firm level in the parentheses. ***, ** and * Significant at 1, 5 and 10 percent level, respectively.

4.A.2 Theoretical Derivations

The profit function of a firm is given as

$$\pi = R\Big(L(E)\Big) - W\Big(E, L(E)\Big)L(E) \tag{4.9}$$

where $R\Big(L(E)\Big)$ represents the revenue, $W\Big(E, L(E)\Big)$ represents the average wage and $L(E)$ represents the employment level. Firm chooses the level of exporting to maximize its profits. We then obtain

$$\frac{\partial R}{\partial L}\frac{\partial L}{\partial E} = \left(\frac{\partial W}{\partial E} + \frac{\partial W}{\partial L}\frac{\partial L}{\partial E}\right)L + W\frac{\partial L}{\partial E}. \tag{4.10}$$

Dividing both sides by $\partial L/\partial E$ yields

$$\underbrace{\frac{\partial R}{\partial L}}_{\text{MRPL}} = \underbrace{\left(\frac{\partial W/\partial E}{\partial L/\partial E} + \frac{\partial W}{\partial L}\right)L + W}_{\text{MLC}} \tag{4.11}$$

The intersection of MRPL and MLC shown in above equation determines the monopsony equilibrium for employment and wage. Here the left hand side of the equation represents the marginal revenue product of labor and the right hand side of the equation represent the marginal labor cost.

I reorganize the Equation (4.10) to obtain elasticities as

$$MRPL\frac{\partial L}{\partial E}\frac{E}{L}\frac{L}{E} = \left(\frac{\partial W}{\partial E}\frac{E}{W}\frac{W}{E} + \frac{\partial W}{\partial L}\frac{L}{W}\frac{W}{L}\frac{\partial L}{\partial E}\frac{E}{L}\frac{L}{E}\right)L + W\frac{\partial L}{\partial E}\frac{E}{L}\frac{L}{E}. \tag{4.12}$$

I denote the employment elasticity as $\rho^L = \frac{\partial L}{\partial E}\frac{E}{L}$, wage elasticity as $\rho^W = \frac{\partial W}{\partial E}\frac{E}{W}$ and labor supply elasticity as ε^{-1}. Using these elasticities, then above equation becomes

$$MRPL\rho^L\frac{L}{E} = \left(\rho^W\frac{W}{E} + \frac{1}{\varepsilon}\frac{W}{L}\rho^L\frac{L}{E}\right)L + W\rho^L\frac{L}{E}. \tag{4.13}$$

Simplifying the equation yields

$$\frac{MRPL}{W}\rho^L = \rho^W + \frac{1}{\varepsilon}\rho^L + \rho^L \tag{4.14}$$

and we finally have the Equation (4.6)

$$\frac{MRPL - W}{W} = \frac{1}{\varepsilon} + \frac{\rho^W}{\rho^L}. \tag{4.15}$$

4.A.3 Variable Definitions

This section provides the details of variable definitions with their codes in the ESEE dataset.

- Exports (VEXPOR): Variable which records the value of exports in Euros.

- Labor Costs (CP): Account 64 (PGC). It records gross salaries and wages, compensations, social security contributions paid by the company, the contributions made to supplementary pension systems and other social expenses. In Euros.

- Amount paid in compensations (IIND): Amount in thousands of pesetas of the compensation paid for lay-offs, early retirements or voluntary redundancies included in labor costs. In Euros.

- Employment (PERTOT): Total personnel employed at the company on December 31st.

- Wage: (CP-IIND)/(PERTOT)

- Sales (VENTAS): Account 70 (PGC). It includes the sales of goods, the sales of transformed products (finished and half-finished), the provision of services and other sales (packages, packaging, byproducts and waste), rappels and sales returns excluded. Units: Euros.

- Labor costs: CP-IIND

- Labor share: (CP-IIND)/(VENTAS)

- Labor productivity: VA/PERTOT

- Skill-intensity = PIL/100

- High-skill workers: PERTOT*PIL/100

- Low-skill workers: PERTOT - (PERTOT*PIL/100)

- Proportion of temporary workers (PEVEN): Percentage which the eventual personnel represents on total personnel employed at the company on December 31st.

- Temporary workers: PEVEN/100*PERTOT
- Imports (VIMPOR): Variable which records the value of imports in Euros.
- Domestic sales: VENTAS-VEXPOR
- Capital investments (INBE): Accounts 212,213,214,215,216,217,218 and 219 (PGC). It is defined as the sum of the purchases of information processing equipment, technical facilities, machinery and tools, rolling stock and furniture, office equipment and other tangible fixed assets. In Euros.
- Value-added (VA): It is defined as the sum of the sales, the variation in stocks and other management income, minus the purchases and external services. Units: Euros.

Chapter 5

Conclusion

In this thesis, I investigated the implications of international trade at the firm-level. The chapters attempt to understand the causes and consequences of firm behavior involved in trade and foster the knowledge in trade literature. Based on a rich micro dataset, studies in this dissertation thesis document substantial information about trading firms that actually determine the international trade flows.

5.1 Main Findings

Chapter 2 documents that robot adopting firms increased their foreign sourcing activities (foreign outsourcing and foreign vertical integration) while did not change their domestic sourcing activities (domestic outsourcing and domestic vertical integration) between 2006 and 2016. Hence, we do not find a systematic reshoring activity in Spain during this period. The estimations remain robust when we control for trade and input cost shocks as well as the substitution between foreign and domestic sourcing strategies.

Our sample reveals that a significant proportion of the firms are involved in sourcing strategies. While the ESEE dataset includes the variables of imports from low-income countries, it does not distinguish the suppliers' country of origin and we can only identify whether they are located in a foreign country or in Spain. Our estimations using the imports from low-income countries still correspond to our main findings.

We develop a theoretical model that focuses the cost advantage of robot adoption and reshoring decisions to explain the mechanisms of our findings. In our model, reshoring decision depends on production and investment costs for producing intermediate inputs in home country. We show that the firm might be sourcing more intermediate inputs from suppliers if robots and supplier's workers are complements whereas the firm sources less intermediate inputs if robots and supplier's workers are substitutes. On the other hand, sourcing is more profitable when producing intermediate inputs with robots is costlier than purchasing from suppliers.

The related literature provides mixed results for reshoring depending on the country and the type of dataset (employee level, firm-level or industry-level). The findings of some studies give support for reshoring but their analyses do not rely on firm-level dataset, i.e. they are not able to identify firm-level robot adoption and intermediate input trade between firms. Other studies find no such evidence on reshoring or even document that robots raised imported intermediate input trade, just as in this analysis. Therefore, more empirical evidences are needed to test the external validity of our study and explicitly understand the dynamics behind the decisions on sourcing strategies of robot adopters.

In Chapter 3, I find that in response to REER devaluations, higher share of exports to low-income destinations in sales reduced the productivity and upgrading efforts of firms. In contrast, REER devaluation did not affect the share of exports to high-income countries in sales, which are predominantly OECD countries that use the same currency with Spain (Euro), and did not experience a differential change in terms of international competitiveness. The regression results are robust to input cost shocks and financial health of the firms.

The findings in this chapter are consistent with the quality sorting hypothesis that links product quality to firm productivity. According to this literature, more productive firms would utilize higher quality inputs (high-skilled workers, better technologies and higher quality materials) and produce higher quality output. Low-income countries are typically characterized by consumers' lower willingness to pay for high quality products, lower competition and limited technology and skilled workers. Aligned with the theoretical predictions and evidences from the previous literature, the findings suggest that firms increasingly exporting to low-income countries due to REER devaluations downgraded their quality.

In my estimations, I use various measures for productivity such as patents, R&D investments, labor productivity, product and process innovations. My regression results remain robust along all these measures of productivity improvements. The dataset used in the analysis provides information about firms' involvement in collaborations with research institutions, competitor firms, universities, suppliers, customers and whether firms received the support from external advisors and experts on technology use. The findings suggest that firms did not only experience a decline in productivity, they even reduced their efforts for upgrading as well.

In Chapter 4, I develop a model for measuring the effect of a firm activity on labor market monopsony power. The method I propose extends the standard monopsony model that estimates labor supply elasticity. Different than conventional approach in which employment is assumed to be the function of wage, my approach relies on the assumption that the firm activity has an impact on labor demand of the firm and wage can be affected by both the firm activity and labor demand. The method I propose can be applied to any study that aims to investigate the impact of a firm activity on labor market monopsony power.

Using this model, I study how exporting changed monopsony power of firms in Spain between 1996 and 2007. Exploiting China's accession to WTO, the results from difference-in-differences estimations suggest that firms with larger exports raised their labor market monopsony power by paying around 39-49% of marginal revenue product to their workers and reduced wages of their employees by 36-45%. Hence, more intensely exporting manufacturing firms in Spain after 2001 increased their monopsony power and these changes were not driven by sectoral or regional developments. The estimation results are robust when I control for imports, domestic sales and capital investments.

I also find that more intensely exporting firms experienced a fall in labor share. Exporting firms additionally decreased their labor productivity, which is in line with higher monopsony power because employees would lose their bargaining power in wage setting if they become less attractive to competitor firms as they become less productive. Finally, the results indicate that higher exports after 2001 induced higher demand for low-skilled and temporary workers while firms' demand for high-skilled workers did not change.

5.2 Discussion and Policy Implications

The impacts of automation technologies on labor market conditions in developing countries have been the areas of intense policy debate. Chapter 2 in this thesis provides more evidence on this subject. In contrast to the expectations of reshoring from low-income countries, I discover that robot adopting firms purchased more intermediate inputs from foreign suppliers, i.e. labor saving technologies had positive impact on international trade. The concerns over reshoring coincide with the growing discontents over globalization. However, my estimation results support the argument of Antràs (2020) in which institutional settings and political backlash against globalization might be the main challenges for the future of trade rather than new technologies.

The emergence of new technologies, the 2008 global financial crisis, rising geopolitical tensions, COVID-19 pandemic, Russia-Ukraine war and the impacts of global warming led to a greater demand for resilience in international trade. Many economists recently called for rethinking on globalization and new concepts in trade policy emerged such as friendshoring, nearshoring and reshoring.[1] The deceleration in the growth of the world trade-to-GDP ratio since the 2008 financial crisis is apparent. However, there is yet limited evidence on deglobalisation and the decline in global trade reflects a slowdown rather than a reversal because it has been temporary and small (e.g. Economist, 2019; Antràs, 2020; Goldberg and Reed, 2023).

The massive growth in world trade during the last decades was not specific to developed countries. The changing patterns of international trade had implications in both high-income and low-income countries. Integration of developing countries into the world economic system thoroughly contributed to rapid growth of international trade flows and increased the share of low-income countries in world exports from early 1990s until the 2008 financial crisis (Dorn and Levell, 2021). Firms in developing economies participated in GVCs, created jobs, attracted investments from rich economies, promote economic development and reduced poverty. Hence, engagement of firms in developing economies with world trade has been vital to improvements in global welfare.

Advocates of free trade highlight the gains from trade for consumers, firms, industries and regions. Previous studies showed that international trade increases productivity growth at the firm and industry level, which is considered to be the primary factor for economic development. Yet, the findings in Chapter 3 underscore that exporting might induce productivity improvements for firms conditional on market destination. Depending on the characteristics of the market destina-

[1] *Friendshoring* refers to moving production to geopolitical allies. *Nearshoring* refers to shifting the production processes to less expensive and geographically closer locations. *Reshoring* refers to bringing the production back to home country.

tion, exporting may or may not enhance the productivity of firms or encourage them for upgrading efforts. Hence, policymakers might take into account the consumer demand and market structure of export destinations in trade agreements to ensure the gains from trade.

It is important to point out that the results of this chapter should not induce a scepticism towards free trade. Contrarily, from a policy perspective, providing incentives to less competitive industries in developed economies for exporting to low-income countries more intensely can encourage firms to upgrade their technology and skills more effectively. The study reminds policymakers that creating opportunities for firms to access a wider range of international markets might induce substantial benefits for some industries.

The findings in Chapter 4 call for the modernization of antitrust laws, making them more suitable to labor markets. A growing literature discovers the presence of monopsonistic labor market conditions and its consequences. Researchers have recently been studying on how to identify the channels through which trade might affect the labor market monopsony power of firms. Policymakers can pay more attention to these new evidences in the literature and correct the market failures that lead to imperfect competition in labor markets. Improving the labor market policies can ensure that the gains from trade are distributed fairly between employers and employees.

In this chapter, I investigate China's integration to international trade system, which had substantial impacts on labor markets across many industries around the world. There is no doubt that export oriented industries benefited from larger market, created jobs and experienced productivity improvements. Alongside of such benefits, previous studies also found that import competition from China is related to job losses for low-skilled workers in the US and the EU (Autor et al., 2016), particularly in those countries that ran a trade deficit with China (Dorn and Levell, 2021) and increased monopsony power of firms in labor market (Caselli et al., 2021). Contributing to this literature, my analysis documents that exporting firms increased their labor market monopsony power after China's accession to WTO.

The world economy experienced a unique set of economic and political developments at both national and international level during the last decades. Since countries multilaterally decided to cooperate on trade in 1990s, advocates of free trade emphasized closer global economic integration and the power of economic interdependence across borders. While tariffs on traded goods between the borders fell significantly, massive technological improvements helped firms to reorganize their production. Today's trade networks are intensely interdependent and international trade network relies on the global division of labor. Significant amount of studies documented the benefits of this economic interdependence and welfare gains from international trade.

Let alone the virtues of trade, massive growth in international trade created winners and losers (e.g. Goldberg and Pavcnik, 2007). For this reason, the world economy today is challenged with protectionist trade policies and shocks to global trade in the last decades underscored the importance of trade policies addressing the resilience (Yellen, 2022).[2] In this regard, technological changes, increasing inequality and the rise of emerging economies recently contributed to growing concerns about trade and associated labor market policies. While nations all around the world benefited greatly from the international trade, empirical studies suggest that trade had unequal distributional effects in labor market during the period of globalization, particularly in developing countries (Goldberg and Pavcnik, 2016). Hence, labor market policies can be aligned with trade policies in order to mitigate the disruptions in labor market.

5.3 Future Research

Substantial progresses in understanding trade patterns have been made in the last two decades as economists focused more on firm behavior but many questions in both theoretical and empirical trade literature remain unexplained. Trade literature does not yet yield conclusive evidences for the subjects studied in this thesis. In the future research projects, I consider addressing related topics and test the external validity of the findings because they are highly relevant to current policy debates.

In Chapter 2, I studied the impact of a specific automation technology: industrial robots. However, there are other kinds of automation technologies such as 3D printing and artificial intelligence (AI). The capabilities of AI have been growing massively and posing increasingly large risks on the future of work. In the future,

[2]Trade restrictions in forms of tariffs and other trade barriers are neither beneficial for consumers nor for firms. As we have seen during the US-China trade war, domestically produced goods are usually not perfectly substitute for imported goods and firms are dependent on global supply chains for their production processes (e.g. Fajgelbaum and Khandelwal, 2022).

I consider studying whether advanced technologies increase firms' resilience to shocks in GVCs.

It must be emphasized that the current empirical findings on the topic is yet mixed. Institutional settings, labor market conditions, patterns of international trade or the economic structure of countries might explain these differences. In the future research agenda, it would be also useful to test the external validity of the findings in this paper and explore the mechanisms leading to varying results in the literature.

Chapter 3 in this thesis examined firms performance of exporting firms conditional on export destination. However, the findings in this study raise further questions to be answered in the future research. Do different levels of competitiveness across export markets determine the upgrading efforts of firms? To what extent does the willingness to pay for quality affect firm performance? How do the market structure and consumer preferences affect firm upgrading? Answering these questions might provide us with substantial amount of information about the relationship between market structure, consumer preferences and firm upgrading.

In Chapter 4, I studied a rapidly growing literature of labor market monopsony. I consider applying the method developed in this chapter to other settings that may be related to labor market monopsony power in the future research works. The advantage of this method is its generality such that the impact of any firm behavior on labor market monopsony power can be examined.

Using the proposed framework, I am currently working on a research with a co-author in which we investigate how R&D investments in Turkey changed the bargaining power between R&D workers and employers. I would like to use it to study the impact of innovation on monopsony power in a future research. The literature focusing on the relationship between innovation and employment analyse employer-employee relationship in the context of rent-sharing. I believe it might be interesting to approach such research question from a different angle.

I also reckon that how importing might affect labor market monopsony power is an intriguing research question. Previous studies documented that access to wider import opportunities might improve firm productivity by reducing input costs. Increased productivity as well as the altering input structure of the firm might increase or decrease the bargaining power of employers.

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